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Validation of the AI-Assisted Second Language (L2) Learning Attitude Scale: Investigating Factor Structure and Psychometric Properties among Iranian Student-Teachers

Azad Allahkarami[1], **Fatemeh Rezaee**[2], and **Rahim Moradi**[3]

1. Corresponding author, Department of Educational Sciences, Farhangian University, P.O. Box 14665_889, Tehran, Iran. A.Allahkarami@cfu.ac.ir

2. Department of Persian Language and Literature Education, Farhangian University, P.O. Box 14665 -889, Tehran, Iran. F.rezaee56@cfu.ac.ir

3. Department of Educational Sciences, Faculty of Humanities, Arak University, Iran.
r-moradi@araku.ac.ir

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Abstract

Given the transformative role of artificial intelligence (AI) in language education, access to valid instruments for assessing learners' perceptions is essential. The present study aimed to localize and validate the AI-Assisted Second Language Learning Attitude Scale among Iranian student-teachers. In this psychometric study, 828 student-teachers from Farhangian University (485 females and 343 males) participated through convenience sampling. Following the forward-backward translation method and cultural adaptation, the instrument was administered to the students. A total sample was divided into two independent sub-samples of 414 participants each. Exploratory factor analysis (EFA) was conducted in SPSS to identify the factor structure, and confirmatory factor analysis (CFA) was performed in AMOS to examine model fit. The EFA results confirmed a two-factor structure comprising cognitive and behavioral components, accounting for 53.94% of the total variance. In the confirmatory factor analysis stage, the initial model was refined, and the final fit indices were highly desirable. Findings from multi-group analysis confirmed the measurement invariance (stability) of the scale's factor structure across male and female students. Cronbach's alpha coefficients and composite reliability indicated high internal consistency. The positive correlation between this scale's scores and AI literacy supported the instrument's criterion validity. The 12-item AI-Assisted L2 Learning Attitude Scale demonstrates robust psychometric properties among Iranian students. This tool can be used as a standardized scale in future research to evaluate learners' readiness and attitudes toward integrating intelligent technologies into curricula.

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Introduction

In the last decade, the rapid emergence and expansion of artificial intelligence (AI) technologies have challenged traditional teaching and learning paradigms and sparked a fundamental transformation in global education systems (Yadav, 2025; Dehbi et al., 2025). AI is defined as the simulation of human intelligence processes by machines, particularly computer systems (Chen et al., 2020). These intelligent processes include reasoning, meaning discovery, generalizing, and learning from past experiences. Generative AI and Large Language Models (LLMs), by offering capabilities such as personalized learning, automated grading, instantaneous feedback, and natural language interactions, have become primary drivers in reshaping educational practices (Maity & Deroy, 2024; Lang et al., 2025; Nasrudin & Hashim, 2025). The integration of AI into educational environments and its combination with learning paradigms is redefining pedagogical strategies (Liu et al., 2024; Yilmaz et al., 2023; Yilmaz & Karaoglan Yilmaz, 2023b).

In this context, the domain of second language (L2) learning has been most significantly impacted by these technologies, given their interactive nature and the critical need for linguistically rich environments. This is primarily because AI's capacity to tailor educational experiences is particularly advantageous, as it aligns with individual learner profiles and needs (Asher & Zweigenbaum, 2020; Jiang, 2022; Son et al., 2023; Yılmaz et al., 2022). Intelligent tools such as chatbots, by leveraging natural language processing, can identify linguistic inaccuracies with high accuracy and provide instantaneous corrective feedback (Bicknell et al., 2023; Liu & Ma, 2023). Research indicates that the successful integration of these emerging technologies into curricula depends not only on technical capabilities but also on learners' psychological readiness and attitudes (Kefuoe & Moeketsi, 2025; Onyema, 2020). In this regard, self-efficacy plays a pivotal role, as belief in one's personal capabilities facilitates the acquisition and use of digital tools (Rosales-Márquez et al., 2025).

A review of the literature reveals that, despite the appeal of AI in education, most early studies focused on technical aspects or general applications of the technology (Lee et al., 2025), with the precise assessment of learner perceptions in specialized domains—such as language education—receiving less attention. Although valuable instruments for measuring students' general attitudes toward AI have been designed by researchers such as Suh and Ahn (2022), these scales are often unable to explain the specific nuances of second language (L2) learning, such as language anxiety, cross-cultural interaction, and the four language skills, due to their generic nature. Recognizing this gap, Wu et al. (2024) recently developed the AI-Assisted Second Language (L2) Learning Attitude Scale, marking a step forward in the specialization of assessment tools in this field. Other research indicates that a positive attitude toward AI is directly related to increased usage in learning and improved language proficiency, which may stem from enhanced thinking abilities, self-efficacy, and motivation (Yilmaz & Karaoglan Yilmaz, 2023a, 2023b).

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However, there is a notable theoretical void regarding the impact of specific L2 learning factors (such as language anxiety, the necessity of cross-cultural communication, and the development of communicative competence) on technology acceptance models. Commonly used attitude scales often overlook the particularities of L2 learning, so a specialized measuring instrument is required. Moreover, psychometric tests are extremely sensitive not only to linguistic particularities but also to cultural and technological access-related factors, so the validity and reliability of these tests across different settings cannot be guaranteed without thorough validation. In the Iranian context of higher education, especially at teacher education universities (where future educators are trained), the importance of understanding attitudes toward AI technologies cannot be overstated. The problem of the lack of a scientifically validated and culturally adapted measuring instrument becomes evident here. In the Iranian higher education system, particularly within teacher education universities (student-teachers) responsible for training the next generation of educators, understanding attitudes toward AI technologies is of paramount importance. The lack of a valid and reliable instrument that has been scientifically translated and culturally adapted poses a major obstacle to educational planning and scientific research in this area.

The present study aims to address this gap through a methodological and instrument-development approach, focusing on the localization and validation of the AI-Assisted Second Language (L2) Learning Attitude Scale (AL2AS) within the Iranian student community. The study makes its contribution mainly through empirical validation of the AL2AS, despite its reliance on existing theories. This has been achieved by developing a sound measurement tool for a very significant yet under-researched population group in development. In terms of methodology, the employment of a sufficiently large number of participants and the conduct of both exploratory factor analyses (EFA) and confirmatory factor analyses (CFA) on two different sub-samples help reduce the risk of overfitting and enhance the robustness of the findings. From a contextual perspective, it allows educational policymakers and scholars to assess learners' preparedness to use smart technologies. Accordingly, the primary objective of this study is to investigate the factor structure, psychometric properties (validity and reliability), and cultural adaptation of the AI-Assisted L2 Learning Attitude Scale among Iranian student-teachers. The research aims to determine whether the proposed two-factor structure adequately fits Iranian society and whether it can be used as a psychometrically valid tool for evaluating learners' attitudes in the education system. To address these gaps, this study was guided by the following research questions:

- What is the factor structure and psychometric evidence (validity and reliability) of the Persian version of the AI-Assisted Second Language (L2) Learning Attitude Scale among Iranian student-teachers?
- Does the AI-Assisted L2 Learning Attitude Scale demonstrate measurement invariance across gender and significant criterion validity through its relationship with AI literacy?

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Literature review

Attitude is defined as a collection of beliefs, feelings, and behaviors toward an entity (Deonna & Teroni, 2015). Within the realm of educational technology, it serves as a critical mediator in users' acceptance of or resistance to modern tools, fundamentally shaping how they interact with technology (Or, 2024). In the context of artificial intelligence (AI), learner attitude is not merely a simple reaction but a multidimensional construct encompassing cognitive and behavioral components. The cognitive component refers to beliefs about the usefulness of AI in language learning, whereas the behavioral component reflects an individual's willingness and intention to use these tools in practice. The significance of this distinction lies in the fact that belief in usefulness does not necessarily translate into actual usage. Attitude intensity can vary among individuals, thereby influencing technology acceptance. In educational settings, this intensity affects how students perceive and accept educational technologies, with performance orientation and technical experience being key factors (Nistor et al., 2019). According to the Unified Theory of Acceptance and Use of Technology (UTAUT), attitude acts as a full mediator, linking performance expectancy, effort expectancy, and behavioral intention, particularly in scenarios where technology use is mandatory (Khechine et al., 2022).

Although UTAUT provides complementary insights into technology acceptance, the present study is primarily grounded in the Technology Acceptance Model (TAM), which serves as the principal theoretical framework for conceptualizing the cognitive and behavioral dimensions of the AL2AS. Self-Determination Theory (SDT) is incorporated as a complementary motivational framework to explain the psychological processes underlying learners' behavioral intentions. According to TAM (Davis, 1989), the perceived usefulness of an application (corresponding to the cognitive dimension of the scale) and the behavioral intention to adopt this technology (behavioral dimension) constitute the basic determinants of technology adoption. According to SDT, when educational technologies satisfy students' basic psychological needs for autonomy, competence, and relatedness, they stimulate higher intrinsic motivation and engagement in the learning process (Deci & Ryan, 1985; Ryan & Deci, 2000; Chen & Jang, 2010).

Furthermore, teachers' attitudes toward educational technologies can moderate their resistance to digital innovations. A positive school culture and an innovative environment can reduce such resistance, highlighting the importance of fostering supportive environments for technology adoption (AL-Takhayneh et al., 2022). It should be noted that students' acceptance of AI for learning purposes depends more on their context-specific attitudes within that educational environment rather than their general attitudes (Yılmaz et al., 2022). In the field of education, students' actual usage of AI tools is significantly shaped by their attitudes toward these technologies (Li, 2023). Attitude mediates the relationship between the diffusion of innovation, technology readiness, and behavioral intention in the context of smart learning. This mediation is vital for the transition from behavioral intention to actual technology usage (Alhammadi et al., 2023).

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Method

Design

The present study is a descriptive survey with an objective and falls under the category of psychometric and instrument development research. The primary aim was to validate the AI-Assisted Second Language (L2) Learning Attitude Scale (AL2AS) within the Iranian higher education context. This research design was adopted to allow for a thorough examination of the tool's factor structure, reliability, and structural validity, enabling the replication of the research and the reproduction of the results.

Participants

The target population consisted of student-teachers at Farhangian University during the 2024–2025 academic year. Convenience sampling was employed to recruit participants, and participation was voluntary. A total of 828 individuals participated in the study (485 females and 343 males; age range: 18–26 years; mean age: 21.18, SD = 1.89). To enhance the validity of the factor analyses and prevent overfitting, the total sample was randomly divided into two independent sub-samples of 414 participants each; the first sub-sample was used for EFA and the second for CFA.

Instrumentation

The primary instrument used was the AI-Assisted Second Language (L2) Learning Attitude Scale (AL2AS). This scale, originally developed by Suh and Ahn (2022) and adapted for the L2 context by Wu et al. (2024), was selected for its specialized focus on cognitive and behavioral components relevant to language education. The 12-item scale is categorized as follows:

- Cognitive Component: 6 items measuring learners' beliefs, perceptions, and evaluations regarding the usefulness and effectiveness of AI in L2 learning.
- Behavioral Component: 6 items evaluating learners' willingness, intention, and practical readiness to use AI tools in the L2 learning process.

Data Collection Procedure

Data were collected online on a voluntary basis. Before the questionnaire was completed, the research objectives were explained to participants, and they were assured of the confidentiality and anonymity of their data, as well as their right to withdraw at any time. The translation and cultural adaptation process followed the standard forward-backward translation method. Conceptual differences were reviewed and refined by three experts in the English language and psychometrics to ensure linguistic and cultural equivalence. For example, the term "club" (Item 8) was changed to "student scientific association" (Anjoman-e Elmi-e Daneshjooyi), and the phrase "streamlining the L2 learning process" (Item 12) was changed to "facilitating and structuring the L2 learning process" to ensure cultural relevance within the Iranian context.

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Data analysis

Data analysis was performed in two main stages:

Stage One: EFA was executed using Principal Axis Factoring and Promax rotation to identify the initial factor structure. Before EFA, sample adequacy was verified using the KMO index, and the significance of the correlation matrix was assessed via Bartlett's test.

Stage Two: CFA was performed in AMOS using Maximum Likelihood estimation to test the measurement model's fit. The fit indices used included the Chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA).

Additionally, the instrument's reliability was evaluated using Cronbach's alpha and composite reliability (CR). Structural validity was assessed using the Fornell-Larcker criterion for convergent and discriminant validity, and criterion validity was confirmed through the relationship between the scale and AI literacy.

Findings

A total of 828 student-teachers participated in this study. Of this number, 485 (58.6%) were female, and 343 (41.4%) were male. The participants' ages ranged from 18 to 26 years, with a mean age of 21.18 years (SD = 1.89). Regarding the distribution of academic majors, the most frequent was Elementary Education (n = 269, 32.5%), followed by Persian Literature (n = 220, 26.6%) and English (n = 80, 9.7%). Additionally, 60 participants (7.2%) were studying Health, 52 (6.3%) Arabic, 48 (5.8%) Theology, and 47 (5.7%) Counseling. In contrast, the lowest frequencies were attributed to Educational Affairs (n = 27, 3.3%) and Social Education (n = 25, 3%).

In terms of technology user experience, the results indicated that the vast majority of participants (96.1%) had experience with artificial intelligence (AI) tools, with only 32 individuals (3.9%) lacking prior experience. Regarding the specific use of AI for writing, 467 students (56.4%) reported using these tools, while 361 (43.6%) had never used AI for writing. The evaluation of participants' second language (L2) proficiency levels revealed that the highest frequency was at the intermediate level (n = 423, 51.1%). The remaining participants were categorized into beginner (n = 311, 37.6%) and advanced (n = 94, 11.4%) levels. This diversity in demographic characteristics and the appropriate distribution of the sample across various proficiency levels and academic majors strengthen the internal validity and robustness of the psychometric analyses of the findings derived from the scale validation.

To identify the factor structure of the AI-Assisted Second Language (L2) Learning Attitude Scale, an EFA was performed on data from the first group (n = 414). First, sampling adequacy and prerequisites for performing factor analysis were examined. The Kaiser-Meyer-Olkin (KMO) value was reported as 0.906. Since this value is greater than 0.9, the adequacy of the

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sample size for performing a factor analysis is considered excellent. Additionally, the Chi-square value in Bartlett's test of sphericity (2491.024) was significant at the 0.001 level (df = 66), indicating the necessary correlation among items to identify the factor structure. Prior to the factor analysis, the univariate normality assumption was checked for all 12 items of the scale. The results showed that skewness values ranged from -1.119 to 0.468 and kurtosis values ranged from -0.627 to 0.803. Since all these values fall within the accepted ranges for univariate normality, it can be concluded that the data exhibit acceptable univariate normality. Accordingly, the use of Principal Axis Factoring for EFA and Maximum Likelihood estimation for CFA is justifiable, considering the appropriate sample size.

Given the exploratory nature of the research and the focus on the common variance of the variables, Principal Axis Factoring (PAF) was used for factor extraction. Based on the initial eigenvalues criterion (Kaiser's criterion), greater than one, two factors were identified. After implementing the factor extraction method, the results indicated that the two factors together explained 53.94% of the scale's total variance. The first factor, with an extracted eigenvalue of 5.16, accounted for 43.04% of the variance, and the second factor, with an eigenvalue of 1.30, accounted for 10.90% of the variance.

To enhance factor interpretability, Promax oblique rotation with Kaiser normalization was applied. The results of the pattern matrix are presented in Table 1. According to the findings, all 12 items exhibited significant factor loadings (above 0.4) on their respective factors, and no items showed cross-loadings. Six items loaded on the first factor (Behavioral Component) and six items loaded on the second factor (Cognitive Component). Factor loadings for the first factor ranged from 0.606 to 0.918, and for the second factor, they ranged from 0.561 to 0.757. Furthermore, the correlation coefficient between the two factors was 0.568.

Table 1

Factor Loadings of the AI-Assisted Second Language (L2) Learning Attitude Scale (N = 414)

No.	Item	Factor Loading	Component
1	I believe that future L2 learning will be closely integrated with AI	0.636	Cognitive
2	I think every student should master the skills of AI-assisted L2 learning	0.757	
3	I consider AI indispensable for L2 learners	0.741	
4	To improve L2 proficiency, I believe it's worthwhile to learn to use AI	0.645	
5	I think I can use AI effectively to assist my L2 learning	0.714	

6	I believe the benefits of AI in L2 learning outweigh the drawbacks	0.561	
7	I would choose a career related to AI-assisted L2 learning	0.640	Behavioral
8	If there is a club related to AI-assisted L2 learning, I would like to join	0.797	
9	I want to watch videos about AI-assisted L2 learning	0.918	
10	I wish to continue learning about how to use AI to assist in L2 learning	0.867	
11	I am willing to use AI to assist my L2 learning	0.721	
12	I aim to employ AI to streamline the L2 learning process	0.606	

Reliability and Internal Consistency To evaluate the internal consistency of the AI-Assisted Second Language (L2) Learning Attitude Scale (AL2AS), Cronbach's alpha coefficients were calculated. The findings showed that the 12-item scale had an overall alpha coefficient of 0.895, indicating high and desirable reliability. Furthermore, the reliability for the cognitive component (6 items) was 0.843, and for the behavioral component (6 items), it was 0.894. Since all alpha coefficients were significantly above the 0.70 threshold and the corrected item-total correlations for all 12 items ranged between 0.494 and 0.721 (exceeding the 0.40 criterion), no items were removed from the analysis. Consequently, the internal consistency of the two-factor structure identified during the exploratory phase was confirmed.

Confirmatory Factor Analysis (CFA) Following the identification of the two-factor structure (cognitive and behavioral) in the exploratory phase, a confirmatory factor analysis (CFA) was conducted on the data from the second sub-sample ($N = 414$) to test the fit of the extracted model and finalize the validation of the factor structure in an independent group. In this phase, Maximum Likelihood estimation was used to evaluate the fit between the theoretical model derived in the previous step and the observed data. The analysis process consisted of two steps: initial model evaluation and model modification.

In the first step, the two-factor model consisting of 12 items was analyzed without applying any modification indices. The fit indices indicated that, while the model showed acceptable overall fit, some indices—such as the Chi-square to degrees of freedom ratio (CMIN/DF = 4.32) and the Root Mean Square Error of Approximation (RMSEA = 0.090)—did not reach optimal levels. The values for other indices at this stage were CFI = 0.936 and TLI = 0.921.

To further evaluate potential sources of localized model misfit, modification indices were examined solely as diagnostic indicators. Error covariances were retained only when supported by clear theoretical and linguistic justification rather than statistical improvement alone (Kline,

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2023). Accordingly, three theoretically defensible error covariances were specified within the measurement model. Within the behavioral component, a covariance was added between e7 and e8. This is theoretically justified as both items measure a distinct sub-dimension of "long-term, extracurricular commitment" to AI (choosing an AI-related career and joining an AI club), which extends beyond immediate classroom usage. Similarly, the covariance between e10 and e11 is linguistically justified due to their nearly identical phrasing and semantic overlap regarding the immediate personal desire to adopt AI tools. Furthermore, within the cognitive component, a negative covariance was modeled between e1 (Item 1) and e6 (Item 6). Unlike the other cognitive items that focus on direct personal utility, both Items 1 and 6 assess macro-level, generalized evaluations (the inevitability of future integration and a systemic cost-benefit analysis of drawbacks). The negative shared variance reflects a theoretical divergence in these macro-evaluations: anticipating inevitable future integration does not perfectly align with dismissing its potential systemic drawbacks. Therefore, these items capture complementary rather than redundant aspects of macro-level evaluations of AI, explaining why their residual association is negative rather than positive. These residual covariances therefore reflect theoretically meaningful shared variance that was not fully captured by the latent constructs, rather than arbitrary data-driven model modifications. In total, three theoretically justified residual covariances (e7–e8, e10–e11, and e1–e6) were incorporated into the final measurement model. The comparison of fit indices between the initial and modified models is provided in Table 2.

Table 2

Comparison of Fit Indices for the Initial and Modified Attitude Scale Models (N = 414)

Fit Index	Symbol	Initial Model	Modified Model	Fit Criterion
Chi-square to degrees of freedom ratio	chi2/df	4.323	2.816	<3
Comparative Fit Index	CFI	0.936	0.967	≥ 0.90
Tucker-Lewis Index	TLI	0.921	0.957	≥ 0.90
Goodness of Fit Index	GFI	0.910	0.944	≥ 0.90
Root Mean Square Error of Approximation	RMSEA	0.090	0.066	<0.10
Root Mean Square Residual	RMR	0.051	0.043	<0.05

As shown in Table 2, the application of modifications resulted in significant improvements across all fit indices. The chi2/df ratio fell below the critical threshold of 3, and the RMSEA reached an optimal level of 0.066, indicating an excellent fit between the modified model and the observed data. Based on the obtained results, the final confirmatory factor analysis (CFA) model is presented in Figure 1. This figure illustrates the standardized factor loadings for each item and the correlation between the cognitive and behavioral components.

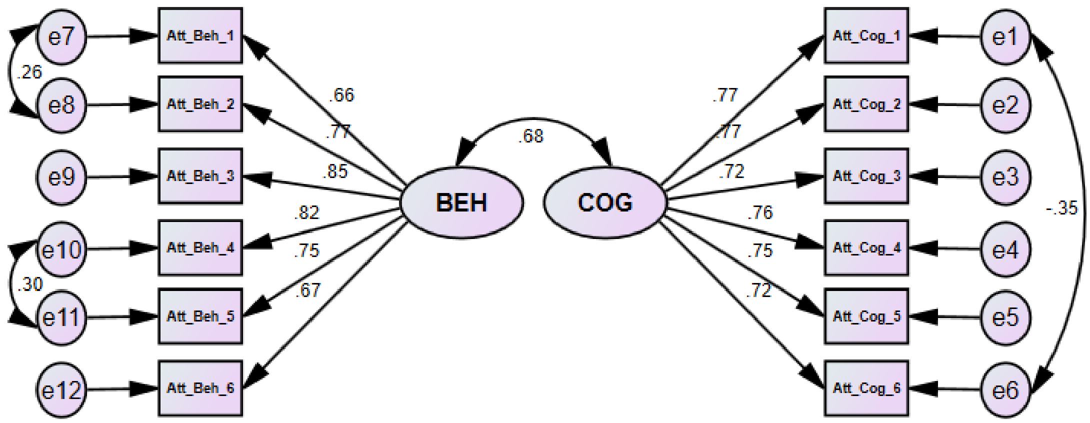

Figure 1. *Final Confirmatory Factor Analysis (CFA) model of the AI-Assisted Second Language (L2) Learning Attitude Scale (N = 414)*

Following the confirmation of the model fit, standardized factor loadings and t-values were estimated for the final model. The results of this analysis are reported in Table 3.

Table 3

Standardized Factor Loadings and t-values for the Final Measurement Model (N = 414)

Latent Factor	Item	Standardized Loading	t-value (C.R.)	p-value
Behavioral Component	Att_Beh_1	0.66	---	---
	Att_Beh_2	0.77	15.48	0.001
	Att_Beh_3	0.85	14.13	0.001
	Att_Beh_4	0.82	13.74	0.001
	Att_Beh_5	0.75	12.86	0.001
	Att_Beh_6	0.67	11.73	0.001
Cognitive Component	Att_Cog_1	0.77	---	---
	Att_Cog_2	0.77	15.74	0.001
	Att_Cog_3	0.72	14.74	0.001
	Att_Cog_4	0.76	15.65	0.001
	Att_Cog_5	0.75	15.26	0.001
	Att_Cog_6	0.72	12.66	0.001

The results in Table 3 indicate that all standardized factor loadings are at a desirable level (above 0.50). Furthermore, the t-values (Critical Ratio) for all paths were significant at the 0.001 level ($p < 0.001$), demonstrating robust construct validity for the 12-item scale within the Iranian population. To conduct a more rigorous evaluation of the scale's psychometric properties during the confirmatory phase, Composite Reliability (CR) and Average Variance Extracted (AVE) were utilized in addition to Cronbach's alpha. CR is considered a more suitable alternative to alpha in structural equation modeling (SEM) and should exceed 0.70. Additionally, the AVE index serves as an indicator of convergent validity, with values above 0.50 being considered desirable. The results of these calculations are presented in Table 4.

Table 4

Composite Reliability and Convergent Validity Indices of the Attitude Scale

Component	Number of Items	Cronbach's Alpha	(CR)	Average Variance Extracted (AVE)	Status
Cognitive Component	6	0.843	0.884	0.560	Optimal
Behavioral Component	6	0.894	0.888	0.572	Optimal
Total Scale	12	0.895	—	—	Optimal

As shown in Table 4, all CR values are significantly higher than 0.7, and AVE values exceed the 0.5 threshold. These findings indicate that the items of each component demonstrate high internal consistency and effectively explain their respective latent constructs. In other words, the convergent validity and structural reliability of the AI-Assisted Second Language (L2) Learning Attitude Scale were definitively confirmed in the target population. To investigate discriminant validity and ensure the distinctiveness of the latent constructs, the Fornell-Larcker criterion was applied. According to this criterion, discriminant validity is established when the square root of the average variance extracted (AVE) for each factor exceeds the correlation coefficient between that factor and any other factors in the model. As illustrated in Table 5, the square root of the AVE for the cognitive component (0.748) and the behavioral component (0.756) is greater than the correlation between the two components (0.68). This finding demonstrates that each scale dimension measures a distinct and independent construct, supporting the model's discriminant validity.

In the final step, the relationship between AI literacy and the total sample ($N = 828$) was examined. Pearson correlation analysis revealed a strong, direct, and positive relationship between these two constructs ($r = 0.733$, $p < 0.05$). This suggests that students with higher AI literacy possess more positive attitudes toward integrating this technology into the L2 learning process. The alignment of this high correlation with the structural indices supports the scale's criterion validity and practical application within the Iranian student population. Furthermore, to evaluate the stability of the factor structure across genders, a measurement invariance analysis was conducted. The results showed that at the metric invariance stage, the change in the Incremental Fit Index (Delta IFI) was 0.009, which is below the 0.01 threshold, indicating equivalent factor loadings between the groups. This finding confirms that the AL2AS instrument measures AI attitude constructs without gender bias among Iranian students.

Discussion

The present study was conducted to validate and investigate the psychometric properties of the AI-Assisted Second Language (L2) Learning Attitude Scale (AL2AS) among 828 Iranian student-teachers. Findings from exploratory and confirmatory factor analyses indicated that the two-factor structure of the scale, consisting of cognitive and behavioral components, demonstrates a highly desirable fit in the Iranian population. This 12-item structure explained 53.94% of the total variance, demonstrating the instrument's high capability for assessing the attitude construct. The confirmation of the two-factor structure in this study is consistent with the study by Wu et al. (2024), who identified a similar structure (cognitive-behavioral) among Chinese students. The identification of these two components as the core pillars of attitude is also consistent with Davis's (1989) Technology Acceptance Model (TAM), which recognizes perceived usefulness (cognitive component) and behavioral intention (behavioral component) as primary drivers of technology adoption.

In this framework, perceived usefulness is the primary predictor of attitude. The present findings suggest that Iranian students develop a positive attitude toward AI once they develop the cognitive belief that this technology can facilitate demanding language learning processes and enhance their efficiency. In other words, attitude in this educational context is the result of a rational evaluation of the tool's utility rather than a mere emotional reaction. The confirmation of the two-factor structure (cognitive and behavioral) in this study points to the conceptual stability of the AI-Assisted L2 Learning Attitude Scale across different cultural contexts. These results indicate that the foundation of language learners' attitudes toward AI—regardless of linguistic and geographical differences—is built on two pillars: belief in efficacy and a willingness to engage in practical interaction. Furthermore, the clarity and simplicity of the scale's items enabled Iranian students to understand the concepts presented, as reflected in the model's optimal fit.

The high item loadings for items related to the desire for further learning and the practical utilization of AI indicate the dynamism of the behavioral component in the studied population. This result is theoretically consistent with the Self-Determination Theory (Deci & Ryan, 2012); it is possible to assume that by providing individualized experiences, AI can help satisfy the needs of students for autonomy and competence (Maity & Deroy, 2024; Lang et al., 2025; Nasrudin & Hashim, 2025), and hence contribute to positive behavioral intentions. This behavioral excitement opens an interesting premise for future investigation – namely, that students might view AI not only as a supplementary aid but also as something that could drive independent learning (He, 2025). Nevertheless, since the present study investigated behavioral intentions and attitudes rather than the actual outcomes of independent learning and the satisfaction of the need for autonomy, the above assumptions remain purely hypothetical and should be empirically investigated in future research. The fit indices obtained in the confirmatory factor analysis phase indicated that the instrument's structural model is at a highly desirable level.

The use of a large sample (N = 828), divided into two independent subsamples for EFA and CFA, strengthens the robustness of the psychometric findings by reducing the risk of overfitting. Moreover, CR coefficients and average variance extracted values, both exceeding standard thresholds, provided further evidence of the instrument's ability to accurately measure the intended latent constructs. Another key finding was the strong, direct, and positive correlation between scale scores and AI literacy. This result confirms that student-teachers' positive attitudes toward integrating AI into language education are rooted in their technical knowledge and digital capabilities, and that technological readiness plays a key role in reducing learner resistance (Nasrudin & Hashim, 2025).

As noted in similar studies, technical knowledge and skills enhance user confidence when encountering innovations (Rosales-Márquez et al., 2025). This finding implies that to improve students' attitudes toward AI, merely promoting its benefits is insufficient; rather, their digital literacy should be enhanced through technical training so that a sense of capability replaces fear of technological complexity. This is consistent with recent theories emphasizing the role of technological readiness in the adoption of innovations. Furthermore, the confirmation of metric invariance in this study demonstrated that the factor structure of the AL2AS remains stable across both male and female students. This aligns with theoretical foundations that emphasize the need for bias-free evaluation of technological tools and ensures that any future score differences stem from genuine differences in attitude rather than flaws in the measurement instrument.

Conclusion

This study validated the Persian version of the AL2AS within the Iranian higher education context. The final results indicated that this 12-item scale is a robust instrument for assessing learners' psychological readiness to engage with artificial intelligence (AI) transformations in language education. The Iranian version of the AL2AS, with its robust psychometric properties and gender invariance, is a valid tool for Iranian researchers. Based on the findings of this research, policymakers at teacher education universities can use this instrument to evaluate student-teachers' readiness before implementing smart language education initiatives.

Given the high factor loadings of the behavioral items, it is recommended that language training courses be designed to focus on the practical application of AI tools, such as chatbots, to strengthen students' behavioral inclination to use these technologies. Despite the measure's promising psychometric qualities, the present study uses convenience sampling, which may introduce bias into the sample. In particular, a considerable majority of participants (96.1%) had previously used AI tools. The high level of technology use may have led to a positive shift in the average attitude scores obtained from the study. Thus, it can be assumed that this result cannot be generalized to populations that lack such extensive knowledge of technologies and access to them. It is recommended to investigate the instrument's ability to predict L2 success.

Bio-data

First Author: Designed and conducted the research procedures, supervised the psychometric analyses, reviewed the final draft, and performed the necessary revisions.
Second Author: Contributed to the data collection process and assisted in the initial literature review.
Third Author: Assisted in data collection and provided methodological support.
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