Razi University

Technology Assisted Language Education

ISSN: 2981-1465

Homepage: https://tale.razi.ac.ir

Evaluating Extended TAM Predictors of AI Chatbot Adoption: A Comparative Study of Iranian and Iraqi EFL Learners

Fatima Wahbi Barban[1], Saman Ebadi[2], Ahmed Rawdhan Salman[3]

[1]Department of English Language and Literature, Faculty of Humanities, Razi University, Kermanshah, Iran, rezaaliabadi2000@gmail.com

[2]Corresponding Author, Department of English Language and Literature, Faculty of Humanities, Razi University, Kermanshah, Iran. s.ebadi@razi.ac.ir

[3]Department of English Language and Literature, Al Mustaqbal University, Iraq. ahmed.rawdhan@uomus.edu.iq

Article Info

Article type:
Research Article

Article history:
Received August 03, 2026
Received in revised form September 30, 2026
Accepted October 14, 2026
Published online October 30, 2026

Keywords:
Artificial intelligence chatbots; English as a foreign language; Technology Acceptance Model

Abstract

The study examined how university EFL learners in Iran and Iraq use AI chatbots and whether their acceptance differs by nationality, gender, prior experience with language-learning technologies, and frequency of use. The respondents of the study included 120 Iranian EFL learners and 100 Iraqi EFL learners. An online questionnaire was used to collect the data. The eight expanded constructs of the technology acceptance model were subjected to descriptive statistics. Mann-Whitney U tests and a factorial multivariate analysis of variance were conducted to compare Iranian and Iraqi scores, as the construct distributions were not normally distributed. Perceived ease of use, facilitating conditions, and technological complexity showed significant differences. There are no statistically significant country differences were expected for PU, ATT, BI, AU, or PE. Frequency of use varied and helped explain and predict the other constructs, so they were all at least associated with frequency of use. Prior exposure to technology encourages use of a new technology. After correction, only actual use remained linked to nationality, and no corrected construct-specific or overall differences emerged by gender. The results relate to acceptance and perceived learning support, not the size or duration of language gains.

Cite this article: Barban, F., Ebadi, S., & Rawdhan Salman, A. (2026). Evaluating Extended TAM Predictors of AI Chatbot Adoption: A Comparative Study of Iranian and Iraqi EFL Learners. Technology Assisted Language Education, (), -. doi: 10.22126/tale.2026.14609.1204

©The Author(s). Publisher: Razi University

DOI: http//doi.org/10.22126/tale.2026.14609.1204

Introduction

The rapid emergence of generative artificial intelligence (AI), marked by the launch of ChatGPT in late 2022, has altered practices worldwide, including in EFL learning. ChatGPT garnered 100 million monthly active users within two months, achieving incredible adoption that surpasses most technologies in history. Generative AI can offer personalized, interactive support by providing feedback on grammar, vocabulary, writing, and speaking in EFL contexts. Generative AI can enhance learner autonomy, motivation, and engagement (Xiao & Zhi, 2023; Kohnke et al., 2023; Liu & Ma, 2024; Wong, 2024). These affordances mitigate longstanding EFL challenges, including a lack of authentic input, limited opportunities for individualized practice, and teacher availability issues due to large class sizes or low-resource contexts (Belda-Medina & Calvo-Ferrer, 2022; Zou et al., 2023; Punar Özçelik & Yangın Ekşi, 2024).

The Technology Acceptance Model (TAM) (Davis, 1989) is widely used in adoption studies. According to TAM, an individual's perceived usefulness (PU) and perceived ease of use (PEOU) inform their attitudes, behavioral intentions, and actual use of a technology. With extensions such as perceived enjoyment (PE), facilitating conditions (FC), and technological complexity (TC), the model has been found relevant to educational AI (Venkatesh et al. 2003; Granić & Marangunić 2019; Liu & Ma 2024). Research in English as a Foreign Language (EFL) shows that perceived usefulness (PU) and perceived ease of use (PEOU) strongly predict attitudes toward AI tools. User engagement is boosted by perceived enjoyment (PE). Perceived friction (FC) enables use in a variable infrastructure. Friction can also act as a barrier (TC) (Belda-Medina & Calvo-Ferrer, 2022; Zou et al., 2023; Hwang et al., 2025; Sallam et al., 2024).

The two most important TAM constructs are PEOU and PU. In EFL education, the user acceptance of AI-driven tools is critical. PEOU is the extent to which learners find it easy to use technology, while PU refers to the degree to which they believe the technology would enhance their learning. In English as a Foreign Language (EFL) contexts, these constructs are crucial, as learners' perceptions of AI tools' usability can predict their use. To illustrate, Belda-Medina and Calvo-Ferrer (2022) found that Spanish and Polish EFL learners found AI chatbots user-friendly, which enhanced their PU for vocabulary acquisition and conversational practice. Similarly, Liu and Ma (2024) reported that Chinese EFL learners' perceived usefulness (PU) of ChatGPT was related to its ability to provide real-time, personalized feedback that improved their writing and speaking skills. Through perceived ease of use (PEOU), less tech-savvy users were able to accept it as useful.

The TAM was extended to include perceived enjoyment (PE), facilitating conditions (FC), and technological complexity (TC) to better capture technology adoption in contemporary settings (including AI-powered tools in EFL) (Venkatesh et al., 2003). Perceived enjoyment is the pleasure a user derives from using technology. It promotes learners' engagement with AI tools. For example, Liu and Ma (2024) reported that the behavioral intention of Chinese EFL learners to use ChatGPT for informal language learning was increased by enjoyment of the interactivity and responsiveness. Similarly, Athanassopoulos (2023) reported that learners in

multilingual classrooms enjoyed using ChatGPT for writing tasks, which motivated them. PE contributes to greater engagement with AI tools like ChatGPT in EFL classrooms (AbuSahyon, 2023).

Despite the growing popularity of Middle Eastern educational software like ChatGPT (Kucuk, 2024; Derakhshan & Ghiasvand, 2024), research on AI adoption among Iranian and Iraqi EFL learners remains limited. Kucuk (2024), in a rare study conducted in Iraq, revealed that EFL students at Tishk International University valued ChatGPT for grammar instruction, with usage driven by PU and institutional support. However, limited digital infrastructure hindered perceived ease of use (PEOU) and adoption (AU), indicating several contextual barriers (Sallam et al., 2024). Derakhshan and Ghiasvand (2024) studied EFL teachers' perceptions in Iran. The teachers' perceptions were concerning academic dishonesty and creativity. However, they note that no learner-focused studies exist. As a result, this creates a critical research gap (Ma et al., 2024).

The lack of studies focused on learners in Iran and Iraq makes it difficult to understand how cultural and contextual factors affect AI adoption according to the TAM framework (Davis, 1989; Alshare et al., 2011). The collectivist norms in both countries influence PU and social influence. Kucuk (2024) shows that Iraqi learners prefer ChatGPT because it supports group learning. In Iran, respect for knowledge may raise ethical concerns about AI use, according to Derakhshan and Ghiasvand (2024). Different regions show variations in digital literacy and infrastructure. This highlights the need for research to identify specific adoption patterns (AbuSahyon, 2023; Elshaer et al., 2024).

Bridging this gap is necessary to develop AI tools that meet the needs of Iranian and Iraqi EFL learners. Research on the Persian Gulf (Sallam et al., 2024; AbuSahyon, 2023) provides data and regional specifics. However, the socio-economic and cultural contexts of Iran and Iraq are distinct and require their own investigation. Adoption, but can also differ substantially in these countries because of differing gender, resource access, and other factors (Elshaer et al., 2024; Panagiotarou et al., 2020). Consequently, a TAM-based analysis to enhance AI integration strategies is necessary (Ma et al., 2024).

> What are the levels of the extended Technology Acceptance Model constructs—Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (A), Behavioral Intention (BI), Actual Use (AU), Perceived Enjoyment (PE), Facilitating Conditions (FC), and Technological Complexity (TC)—among Iranian university EFL learners using AI chatbots for English language learning?
>
> What are the levels of the extended TAM constructs (as listed in RQ1) among Iraqi university EFL learners using AI chatbots for English language learning?
>
> Are there statistically significant differences between Iranian and Iraqi EFL learners in their levels of the extended TAM constructs when using AI chatbots for English language learning?

To what extent are contextual factors (gender, prior experience with language learning technologies, frequency of AI chatbot use, access to technological resources) associated with the extended TAM constructs and overall acceptance of AI chatbots among Iranian and Iraqi EFL learners?

Method

Design

The researchers used a quantitative design and measured the eight extended TAM constructs and relevant background characteristics of university EFL learners in Iran and Iraq through a cross-sectional online questionnaire. This phase was when construct levels were established in each group, examination of the differences between the groups took place, and selected contextual factors were associated with the multivariate acceptance profile and an overall-acceptance composite. The research method was observational cross-sectional. Nationality, gender, prior experience with technology, and reported exposure to or use of chatbots were measured characteristics, not manipulated factors. So group differences and factorial effects are interpreted as associations. It is not asserted that the measured contextual factors caused acceptance, use, or perceived complexity.

Participants

The target population was university students in Iran and Southern Iraq who use English as a foreign language. Participants were recruited from English departments, language centers, and similarly related programs. Because no exhaustive sampling frame existed, we used convenience and snowball sampling to recruit university learners using AI chatbots. We approached faculty members, online, educational, or peer networks for initial participants, who could then refer other qualified learners. These non-probability procedures are better suited to accessing an emerging and dispersed population, but they do not provide nationally representative samples (Dörnyei, 2007).

The total quantitative sample was 220, comprising 120 respondents in the Iranian dataset and 100 respondents in the Iraqi dataset. There were 130 females (59.1%) and 90 males (40.9%) in the total sample. In Iran, 78 respondents were women and 42 were men, while in Iraq, 52 were women and 48 were men. Eighty-three Iranian and eighty-five Iraqi respondents reported prior familiarisation with language-learning technology.

Chatbot exposure was measured differently in different countries. The Iranian form used four categories for weekly usage, while the Iraqi form included both a four-category familiarity item and a six-category frequency item. Table 1 outlines the directly comparable features and lists the variables that were measured for each country.

Table 1. *Achieved Quantitative Sample and Background Information*

Characteristic	Iran (n = 120)	Iraq (n = 100)	Comparability note
Gender	Women 78 (65.0%); men 42 (35.0%)	Women 52 (52.0%); men 48 (48.0%)	Common variable in both forms
Prior language-learning technology experience	Yes 83; no 36; multiple response 1	Yes 85; no 15	Common concept; one Iranian response requires coding confirmation
Age	Not recorded in achieved dataset	Recorded in age ranges	Not used as a common predictor
Academic degree	Undergraduate 23; BA 48; MA 44; PhD 5	Not recorded in achieved dataset	Country-specific descriptor
Chatbot exposure/use	Four weekly-hours categories	Four familiarity categories and a separate six-level frequency item	Wording and category systems are not equivalent

Note. Counts reproduce the achieved country datasets. Percentages are supplied only where the categories are directly comparable and unambiguous.

Instruments

The online questionnaires began with country-specific background questions. Both questionnaires collected information on nationality, gender, prior experience with technology for language learning, and an indicator of chatbot exposure or use. The Iranian form also captured academic field and degree, weekly hours of ChatGPT use, and optional contact information. The Iraqi version further recorded participants' age group, whether they had previously used a chatbot to learn or practice English, their familiarity with chatbots, and frequency of use.

Extended Technology Acceptance Model Questionnaire

40-item extended TAM questionnaire was the main quantitative instrument. Every statement was rated on a Likert Scale from 1 (strongly disagree) to 5 (strongly agree). The instrument was based on the original TAM constructs proposed by Davis (1989) and the extensions addressing facilitating conditions and use by Venkatesh et al. (2003). The language was adapted to ChatGPT or AI chatbots for learning English.

The device measured eight constructs. PEOU concerns the tool's ease of use and how easy it is to remember. PU refers to the perceived quality, usefulness, opportunities, ability development, and learning environment related to the chatbot. The attractiveness, interestingness, enjoyment, perceived goodness of use of the tool, and belief in its utility were measured. The BI referred to effort, expected future frequency, continuation, likelihood of continuation, and intention to use the chatbot to learn English. For motivation, language skills,

information gathering, cultural understanding, and learning performance, AU measures self-reported use. PE spoke to interest, pleasantness, and enjoyableness. Access to guidance, instruction, assistance, resources, skills, knowledge, and opportunities is covered by FC. The TC metric measured difficulty, effort, complexity, and trouble of learning the chatbot.

Table 2 provides the item allocation used for scoring. The questionnaire was formatted so that the PU heading is just before item 5. Nonetheless, item 5 asks whether it is easy to remember using ChatGPT. As a result, the five-item PEOU scale is completed. PU was awarded from Items 6-10. The instrument and both participant-level datasets include four TC items (Items 37-40).

Table 2. Extended TAM Construct Scoring

Construct	Items	k	Content	Direction
PEOU	1-5	5	Convenience, comprehension, learnability, skill, and memorability	Higher = easier
PU	6-10	5	Learning quality, usefulness, opportunities, ability, and learning environment	Higher = more useful
A	11-15	5	Attractiveness, interest, enjoyment, good idea, and perceived potential	Higher = more positive
BI	16-20	5	Effort, expected future frequency, continuation, likelihood, and intention	Higher = stronger intention
AU	21-25	5	Self-reported use for motivation, skills, information, culture, and performance	Higher = more use
PE	26-28	3	Interest, pleasantness, and enjoyment	Higher = more enjoyment
FC	29-36	8	Guidance, instruction, assistance, resources, skills, and opportunity	Higher = better conditions
TC	37-40	4	Difficulty, effort, complexity, and trouble learning to use the tool	Higher = more complexity

Note. PEOU = perceived ease of use; PU = perceived usefulness; A = attitude; BI = behavioral intention; AU = actual use; PE = perceived enjoyment; FC = facilitating conditions; TC = technological complexity.

Data collection Technique

Construct scores were calculated as averages of their items so that all scores were on the original 1-5 metric. A higher score indicates greater perceived usefulness, positive attitude, intention to use, and facilitating conditions; a higher TC score indicates greater perceived complexity and runs in the opposite direction. TC therefore requires reverse scoring before inclusion in any composite intended to represent uniformly favorable overall acceptance. Given the wording of the instruments and the response context, we estimated internal consistency country-wise using Cronbach's alpha for the two forms. The analysis does not demonstrate cross-country

measurement invariance; therefore, these are comparisons of observed scale scores, not true scores, and do not prove that every item worked the same way across languages and contexts.

Data Analysis

The statistical analyses were conducted in IBM SPSS Statistics, version 26. Descriptive statistics were first calculated for the eight TAM constructs. The results for RQ1 (Iranian sample) and RQ2 (Iraqi sample) were summarized. Because all constructs were retained on the 1-5 response scale, the means could be interpreted relative to the midpoint and the observed variability.

To examine the distributional assumptions for each country, we conducted Kolmogorov-Smirnov and Shapiro-Wilk tests. The scores of Iranians and Iraqis were compared using Mann-Whitney U tests because their distributions were not normal. The test statistic, standardized statistic, and two-sided probability were presented for each construct. The common significance threshold was 0.05. Since there were eight construct comparisons done and the archived RQ3 analysis does not document any multiplicity adjustment, the exact probability values should be interpreted in conjunction with the size and consistency of the observed differences.

RQ4 was tested using a factorial MANOVA. The eight construct scores served as the dependent variables, while nationality, gender, prior exposure to language-learning technology, and a four-level chatbot exposure/use factor served as predictors. Because it is more resistant to unequal cell sizes and departures from homogeneity of covariance matrices, Pillai's trace was used for multivariate tests. The model assessed main effects. Interaction terms were excluded as multiple combinations of country, gender, experience, and exposure/use were under-subscribed.

When a multivariate main effect was statistically significant, follow-up univariate ANOVAs were performed to diagnose the constructs responsible for the effect. The familywise criterion was set at .00625 by dividing .05 by the number of dependent variables. Partial eta squared measured the size of multivariate and univariate effects. A factorial ANOVA utilized the overall-acceptance composite as the dependent variable and the same four contextual predictors. These procedures assess whether the measured contextual factors were associated with the acceptance profile, but they do not test the directional TAM pathways outlined in the original hypotheses. Most notably, the analyses do not estimate whether PU predicts attitude or whether BI predicts AU.

Findings

To answer the first research question as follows:

RQ1: What are the levels of the extended Technology Acceptance Model constructs—Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (A), Behavioral Intention (BI), Actual Use (AU), Perceived Enjoyment (PE), Facilitating Conditions (FC), and

Technological Complexity (TC)—among Iranian university EFL learners using AI chatbots for English language learning?

In this research study, the mean and variability of students' perceptions of the fundamental components of the Technology Acceptance Model (TAM) were computed. Table 3 presents the descriptive statistics for TAM components among Iranian university EFL learners, in descending order.

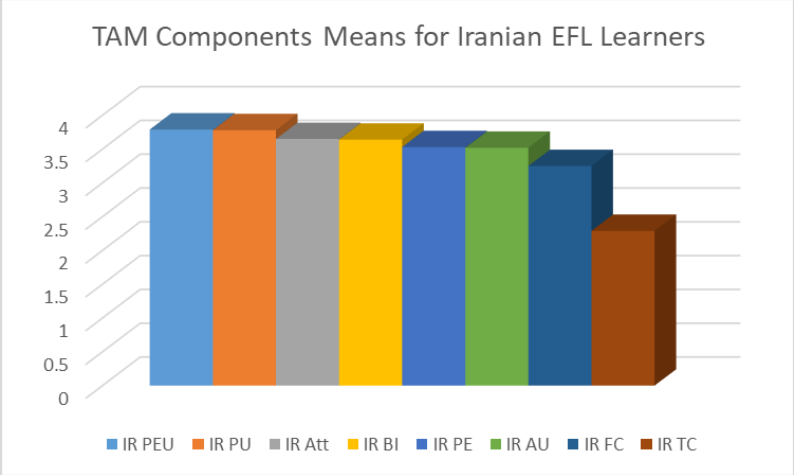
Table 3. *Descriptive Statistics of TAM Components for Iranian University EFL Learners*

	N	Min	Max	Mean	SD	Var
IR Perceived Ease of Use	120	1.00	5.00	3.79	1.11	1.24
IR Perceived Usefulness	120	1.00	5.00	3.78	1.06	1.12
IR Attitude	120	1.00	5.00	3.65	1.07	1.15
IR Behavioral Intention	120	1.00	5.00	3.64	1.07	1.15
IR Perceived Enjoyment	120	1.00	5.00	3.53	1.15	1.33
IR Actual Use	120	1.00	5.00	3.52	1.20	1.45
IR Facilitating Conditions	120	1.00	5.00	3.25	.98	.96
IR Technological Complexity	120	1.00	5.00	2.29	.98	.97

As presented in Table 3, Perceived Ease of Use (PEU) obtained the highest mean score (M = 3.79, SD = 1.11), closely followed by Perceived Usefulness (PU) (M = 3.78, SD = 1.06). Attitudes (M = 3.65, SD = 1.07), Behavioral Intention (BI) (M = 3.64, SD = 1.07), Perceived Enjoyment (PE) (M = 3.53, SD = 1.07), Actual Use (AU) (M = 3.52, SD = 1.20), and Facilitating Conditions (FC) (M = 3.25, SD = 0.98), all clustered above the mid-point of the scale, suggesting moderately positive dispositions and behaviors. Technological Complexity (TC) yielded the lowest mean score (M = 2.29, SD = .98).

A visual representation of the tabulated data (Figure 1) illustrates the hierarchical order of mean scores for the TAM components among Iranian university EFL learners.

Figure 1. TAM Component Means for Iranian University EFL Learners



The second research question revealed the Iraqi Learners' acceptance profile as follows:

RQ2: What are the levels of the extended TAM constructs (as listed in RQ1) among Iraqi university EFL learners using AI chatbots for English language learning?

To examine this research question, the central tendencies and variability of students' perceptions across the core Technology Acceptance Model (TAM) components were calculated. Table 4 presents the descriptive statistics for TAM components for Iraqi university EFL learners in descending order.

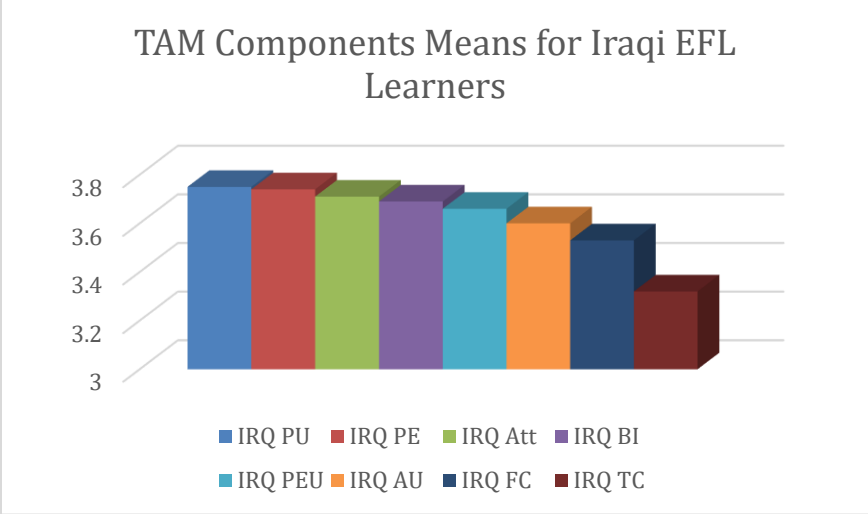
Table 4. Descriptive Statistics of TAM Components for Iraqi University EFL Learners

	N	Min	Max	M	SD	Var
IRQ Perceived Usefulness	100	2.50	5.00	3.75	.64	.41
IRQ Perceived Enjoyment	100	1.33	5.00	3.74	.79	.62
IRQ Attitude	100	1.80	5.00	3.71	.68	.47
IRQ Behavioral Intention	100	1.60	5.00	3.69	.71	.50
IRQ Perceived Ease of Use	100	1.50	5.00	3.66	.71	.50
IRQ Actual Use	100	1.00	5.00	3.60	.76	.58
IRQ Facilitating Conditions	100	1.25	5.00	3.53	.70	.49
IRQ Technological Complexity	100	1.00	5.00	3.32	.94	.89

As portrayed in Table 4, Perceived Usefulness (PU) gained the highest mean score (M = 3.75, SD = .64), closely followed by Perceived Enjoyment (PE) (M = 3.74, SD = .79), Attitudes (M = 3.71, SD = .68), Behavioral Intention (BI) (M = 3.69, SD = .71), Perceived Ease of Use (PEU) (M = 3.66, SD = .71), Actual Use (AU) (M = 3.60, SD = .76), Facilitating Conditions (FC) (M = 3.53, SD = 0.70), and Technological Complexity (TC) (M = 3.32, SD = .94). As noticed, the score means for all components clustered above the mid-point (2.5) of the scale, suggesting moderately positive dispositions and behaviors.

A visual representation of the tabulated data (Figure 2) illustrates the hierarchical order of mean scores for the TAM components among Iraqi university EFL learners.

Figure 2. *TAM Component Means for Iraqi University EFL Learners*



The third research question examined the differences between Iranian and Iraqi learners as follows:

RQ3: Are there statistically significant differences between Iranian and Iraqi EFL learners in their levels of the extended TAM constructs when using AI chatbots for English language learning?

To address this research question, we first obtained descriptive statistics and normality test results to test the assumption of normality for each TAM component separately for Iranian and Iraqi participants. Table 5 presents the respective results.

Table 5. Descriptive Statistics and Normality Test Results for TAM Components

TAM Components	Group	No	M	SD	Var	KS Statistic	KS df	KS Sig.	SW Statistic	SW df	SW Sig.
PEU	Iraqi	100	3.67	0.71	0.51	.113	100	.003	.962	100	.006
	Iranian	120	3.80	1.11	1.24	.198	120	.000	.883	120	.000
PU	Iraqi	100	3.75	0.64	0.41	.113	100	.003	.964	100	.008
	Iranian	120	3.78	1.06	1.13	.173	120	.000	.901	120	.000
Attitude	Iraqi	100	3.72	0.69	0.48	.101	100	.013	.975	100	.051
	Iranian	120	3.65	1.07	1.15	.144	120	.000	.925	120	.000
BI	Iraqi	100	3.69	0.71	0.51	.105	100	.009	.951	100	.001
	Iranian	120	3.64	1.07	1.15	.139	120	.000	.930	120	.000
AU	Iraqi	100	3.61	0.77	0.59	.116	100	.002	.957	100	.002

TAM Components	Group	No	M	SD	Var	KS Statistic	KS df	KS Sig.	SW Statistic	SW df	SW Sig.
	Iranian	120	3.52	1.21	1.46	.153	120	.000	.910	120	.000
PE	Iraqi	100	3.74	0.79	0.63	.117	100	.002	.958	100	.003
	Iranian	120	3.54	1.15	1.33	.180	120	.000	.919	120	.000
FC	Iraqi	100	3.53	0.71	0.50	.121	100	.001	.966	100	.011
	Iranian	120	3.25	0.98	0.97	.074	120	.159	.976	120	.031
TC	Iraqi	100	3.33	0.95	0.89	.212	100	.000	.888	100	.000
	Iranian	120	2.30	0.98	0.97	.096	120	.008	.933	120	.000

KS = Kolmogorov-Smirnov; SW = Shapiro-Wilk.

As shown in Table 5, the normality test results for both groups across all variables were statistically significant when variables were considered in pairs, indicating a violation of normality for all variable pairs. Accordingly, we used the Mann-Whitney U test for subsequent group comparisons, and the results are presented in Table 6.

Table 6. Mann–Whitney U Tests for TAM Components

Components	Total N	Mann-Whitney U	Wilcoxon W	Test Statistic	Standard Error	Standardized Test Statistic	Asymptotic Sig. (2-sided)
PEU	220	7095.00	14355.00	7095.00	467.81	2.34	.02
PU	220	6771.00	14031.00	6771.00	468.60	1.65	.10
Attitude	220	6195.50	13455.50	6195.50	467.76	0.42	.68
BI	220	6240.50	13500.50	6240.50	468.27	0.51	.61
AU	220	6329.00	13589.00	6329.00	468.53	0.70	.48
PE	220	5705.50	12965.50	5705.50	465.75	-0.63	.53
FC	220	4917.00	12177.00	4917.00	469.39	-2.31	.02
TC	220	2491.50	9751.50	2491.50	468.59	-7.49	.00

As the results of Mann-Whitney U tests in Table 6 reveal, there are statistically significant differences between Iranian and Iraqi EFL learners on Perceived Ease of Use ($U = 7095.00$, $z = 2.34$, $p = .02$), Facilitating Conditions ($U = 4917.00$, $z = -2.31$, $p = .02$), and Technological Complexity ($U = 2491.50$, $z = -7.49$, $p < .001$). However, there exists no statistically significant differences in terms of Perceived Usefulness ($U = 6771.00$, $z = 1.65$, $p = .10$), Attitude ($U = 6195.50$, $z = 0.42$, $p = .68$), Behavioral Intention ($U = 6240.50$, $z = 0.51$, $p = .61$), Actual Use ($U = 6329.00$, $z = 0.70$, $p = .48$), or Perceived Enjoyment ($U = 5705.50$, $z = -0.63$, $p = .53$). Based on the information in Table 5, Iranian learners reported significantly higher PEU ($M = 3.80$) than their Iraqi counterparts ($M = 3.67$). However, Iraqi learners reported significantly higher FC ($M = 3.53$) than Iranian EFL learners ($M = 3.25$), and also significantly higher TC ($M = 3.33$) than their Iranian peers ($M = 2.30$).

To answer the fourth research question, what extent do contextual factors (gender, prior experience with language learning technologies, and frequency of AI chatbot use) associate with the extended TAM constructs and overall acceptance of AI chatbots among Iranian and Iraqi EFL learners?

Eight TAM constructs were included in the multivariate analysis of variance (MANOVA). These are perceived ease of use, perceived usefulness, attitude, behavioral intention, actual use, perceived enjoyment, facilitating conditions, and technological complexity. The independent variables were nationality (Iraqi vs. Iranian), gender (female vs. male), previous experience with language learning technologies (yes vs. no), and the level of AI chatbot use (four levels). Pillai's Trace was chosen as the test statistic in this case because it is more robust to violations of homogeneity of covariance matrices as may arise with unequal cell sizes. As small cell sizes in some combinations invalidated the interaction effects, only main effects were examined. The four contextual factors' multivariate estimates are depicted in Table 7.

Table 7. Multivariate Tests of Contextual Factors on Extended TAM Constructs

Effect	Pillai's Trace	F	df1	df2	p	Partial η^2
Nationality	.10	2.90	8	209	.004	.10
Gender	.08	2.27	8	209	.023	.08
Prior experience	.12	3.48	8	209	.001	.12
Frequency of AI chatbot use	.28	2.82	24	633	< .001	.10

Table 7 demonstrates that all four contextual factors have a multivariate and statistically significant effect on the set of extended TAM constructs. The greatest effect was produced by the frequency of AI chatbot use, which explained close to 10 percent of the variance in the linear combination of the dependent variables. Prior experience with learning technologies also had a significant multivariate effect (partial eta squared = .12). Nationality and gender were

also significant but had smaller effect sizes. The findings suggest that each contextual factor had a role in the differences in learner perceptions and acceptance of AI chatbots.

The significant multivariate effects prompted follow-up univariate ANOVAs to determine which TAM constructs drove the differences. To avoid Type I error, a Bonferroni-adjusted alpha level of .00625 (.05/8) was adopted. Table 8 summarizes univariate results for dependent variables analyzed with four predictors.

Table 8. Univariate ANOVAs for Extended TAM Constructs by Contextual Factors

Dependent Variable	Nationality F (1, 213)	p	η^2	Gender F (1, 213)	p	η^2	Prior Experience F (1, 213)	p	η^2	Frequency F (3, 213)	p	η^2
Perceived Ease of Use	3.45	.06	.016	0.12	.731	.00	5.40	.02	.02	9.87	< .001	.121
Perceived Usefulness	5.12	.02	.023	1.23	.26	.00	6.80	.01	.03	6.54	< .001	.083
Attitude	2.10	.14	.010	3.87	.05	.01	4.30	.03	.02	11.20	< .001	.135
Behavioral Intention	0.45	.50	.002	0.89	.34	.00	8.05	.00	.03	7.35	< .001	.093
Actual Use	8.92	.00	.040	1.67	.19	.00	2.85	.09	.01	12.45	< .001	.147
Perceived Enjoyment	3.20	.07	.015	5.34	.02	.02	4.75	.030	.02	8.76	< .001	.109
Facilitating Conditions	6.78	.01	.030	4.12	.04	.01	10.20	.002	.04	10.32	< .001	.125
Technological Complexity	0.67	.41	.003	2.45	.119	.01	12.30	< .001	.054	5.89	.001	.076

Table 8 discusses univariate results, which indicate that frequency of use of AI chatbots is the most stable predictor. It has a significant impact on the eight extended TAM constructs even after Bonferroni correction. The observed largest effects were determined to be on actual use ($\eta^2 = .147$), attitude ($\eta^2 = .135$), facilitating conditions ($\eta^2 = .125$), and perceived ease of use ($\eta^2 = .121$). Students with familiarity with AI chatbots earned higher scores on these constructs.

Prior experience with language learning technologies had significant univariate effects on behavioral intention ($p = .005$, $\eta^2 = .036$), facilitating conditions ($p = .002$, $\eta^2 = .046$), and technological complexity ($p < .001$, $\eta^2 = .054$) after adjustment. This suggests that learners with prior experience found the technology less complex and reported stronger facilitating conditions and behavioral intention to use AI chatbots.

Following the Bonferroni correction, nationality exerted only a significant univariate effect on actual use ($p = .003$, $\eta^2 = .040$). Scores showed that Iranian learners performed slightly higher than Iraqi learners. The gender variable did not reach the adjusted significance level for any

individual dependent variable, although it showed marginal trends for perceived enjoyment and facilitating conditions.

To examine overall acceptance, we created a composite score by averaging the eight extended TAM construct scores. A factorial ANOVA with nationality, gender, prior experience, and frequency of AI chatbot use as predictors showed that frequency of use was the only statistically significant predictor of overall acceptance, $F(3, 213) = 12.41$, $p < .001$, partial $\eta^2 = .15$. Prior experience approached significance, $F(1, 213) = 3.87$, $p = .050$, partial $\eta^2 = .018$, while neither nationality nor gender reached significance.

Together, these results showed that context factors were associated with the multivariate TAM profile, but their relative contributions differed. AI-chatbot familiarity/use was the most reliable predictor across the eight constructs and the sole significant predictor of the overall acceptance composite. Prior experience was related uniquely to behavioral intention, facilitating conditions, and technological complexity. After applying the Bonferroni correction, nationality was associated solely with actual use. Gender, by contrast, showed a significant multivariate effect; however, it did not produce an adjusted construct-specific or overall acceptance effect.

Discussion

The first research question was about the acceptance profile of Iranian learners. Most Iranian learners approved the eight expanded TAM dimensions. Perceived ease of use was rated highest. Perceived ease of use (M = 3.79). The mean was above the midpoint for attitude, behavioral intention, perceived enjoyment, actual use, and facilitating conditions, while technological complexity had the lowest mean. M = The low score on the complexity items should be interpreted as limited perceived complexity and not as a weakness in acceptance.

Ease of use and usefulness align with TAM, which argues that users' judgments of effort and value are vital to technology acceptance (Davis, 1989). The assessment of Granić and Marangunić (2019) concluded that perceived ease of use and usefulness are significant predictors of educational-technology acceptance across learning settings. A similar trend appears in research on generative AI. According to Liu and Ma (2024), the perceived usefulness of communication technologies (mainly WeChat) among Chinese mathematics students has shaped their attitudes toward using their smartphones in the classroom. Similarly, perceived usefulness shaped the behavioral intention, which strongly predicted the reported use of the technologies outside the classroom. According to Hwang et al. (2025), ease of use has a weak direct effect, while usefulness predicts Korean EFL learners' continuance intention. According to Alotaibi et al. (2025), Saudi EFL learners' acceptance was linked to both usefulness and ease of use, but perceived usefulness was more significant for attitude. Findings from Iran corroborate a broader conclusion: learners embrace ChatGPT when they can connect its affordances to familiar language-learning objectives.

The survey assessed perceptions and self-reported behaviors related to meaning, not writing, vocabulary, speaking, or other similar language outcomes. Lo et al.'s (2024) systematic review highlights the importance of distinguishing between increased learning opportunities, personalization, and teacher support and objective outcome measures or skills beyond writing. Current research suggests participants felt AI chatbots helped them learn, but this study does not indicate how much they learned or how long the benefits lasted.

The Iranian profile differentiates personal endorsement from environmental assistance. Participants perceived facilitating conditions as better, but less than ease, usefulness, attitude, and intention. AI chatbots may help learners understand but not provide timely help, advice, access, or aid. According to Granić (2022), educational technology adoption is influenced by facilitating conditions, accessibility, self-efficacy, enjoyment, and complexity. The present study extends this distinction to an under-researched EFL setting. Intuitive interfaces and positive beliefs, alone, do not guarantee that learners have the conditions for informed and sustained use.

The second research question studied the profile of Iraqi acceptance. It examined the profile of Iraqi learners. Among the variables, perceived usefulness had the highest mean (3.75), followed by perceived enjoyment (3.74), attitude (3.71), behavioral intention (3.69), perceived ease of use (3.66), actual use (3.60), and facilitating conditions (3.53). Technological complexity was also above the midpoint (M = 3.32). So the Iraqi group combined favorable judgments of value, enjoyment, and intended use with a clear perception that the technology could be difficult or demanding.

There is a meaningful combination. The friction learners experience should not diminish their perceived usefulness, positive attitude, and behavioral intention. The influence of perceived usefulness, ease of use, social influence, behavioral and cognitive influence, anxiety, and perceived risk on use and attitudes was assessed in the multinational Arab-country study of Abdaljaleel et al. (2024). Sallam et al. (2024) similarly found an association between ChatGPT use and usefulness, ease of use, perceived risks, and psychosocial factors. The research indicates that acceptance is not just a positive or negative judgment. Learners can recognize a system's value and intend to use it, despite doubts about reliability, support, and the effort required to get appropriate results.

The third research question asked whether the two national groups differed across the extended TAM constructs. The Mann-Whitney U tests revealed significant differences in perceived ease of use, facilitating conditions, and technological complexity. Iranian learners considered it easy to use, whereas Iraqi learners considered it easy to use, with facilitating conditions and considerably higher technological complexity. No group differences were statistically significant for perceived use, attitude, behavioral intention, actual use, or perceived enjoyment.

The lack of differences on five constructs is at least as important as the three significant differences. Participants in both groups considered the AI chatbots useful, expressed positive attitudes, intentions, and enjoyment, and reported similar levels of use. This common profile

affirms the cross-context applicability of principal acceptance processes identified in the TAM literature. According to Granić and Marangunić (2019), usefulness and ease are common characteristics of different educational technologies. Additionally, Liu and Ma (2024), Alotaibi et al. (2025), and Hwang et al. (2025) show that EFL learners' acceptance of ChatGPT continues to revolve around perceived value, despite differing structural relationships. The similarity suggests that perceived academic value is not limited to a specific setting.

The fourth research question examined the relationship between nationality, gender, previous experience with language-learning technologies, and frequency of AI-chatbot use and the overall TAM profile and overall acceptance. The eight constructs were found to have statistically significant associations with each factor. Frequent use of AI chatbots was associated with the constructs and was a unique, statistically significant predictor of overall acceptance. Previous experience related to facility conditions, behavioral intentions, and technological complexity. Nationality was related only to actual usage following correction. Gender had a multivariate impact, but its effect on any individual construct or overall acceptance did not meet the adjusted criteria.

The most consistent variable in context was frequency of use. According to frequently experienced users, they find use easier, more useful, and enjoyable, with a positive attitude, intention, actual use, facilitating conditions, and a difference in perception of complexity. This finding is consistent with literature that considers familiarity to be a component of AI literacy. In a recent study, Liu, Darvin, and Ma (2024) found that the learners' beliefs of usefulness developed through experimentation. They also learned to negotiate the affordances and constraints of using generative AI tools. According to Xiao and Zhi (2023), learners have also evaluated output quality. They then change prompts to increase learning value.

Cross-sectional data is not adequate to determine the direction of this association. Frequent use may increase skill and confidence, but learners who already view the chatbot as useful, enjoyable, and easy are likely to use it more. The structural analysis by Liu and Ma (2024) supports a pathway from positive attitudes and intention to actual use, whereas mixed-methods evidence from Liu, Darvin, and Ma (2024) suggests experience may also reshape perceptions. The current result supports a reciprocal process. Simply repeating an idea more frequently will not make it acceptable. It also should not be relied upon so much that it is used indiscriminately.

Experience had a narrower but interpretable association. The identification of the Behavioral Intention, Facilitating Conditions, and Technological Complexity was done after the adjustment. Learners who have engaged in multiple learning opportunities may have prior knowledge of interfaces, troubleshooting, prompt construction, and feedback from automated systems. They may know where to get support, changing their perception of facilitating conditions even if the institutional environment remains the same. According to Alotaibi et al. (2025), longer use and stronger IT skills were associated with more favorable acceptance indicators among Saudi EFL learners. The experience effect suggests that equitable implementation requires more than having access to the same application. The participants have

different experiences with AI-supported tasks, which may influence perceived difficulty and intention to continue the task. Generalization is limited by gender results.

Conclusion

The findings suggest that acceptance depends on perceived educational value, learner experience, task demands, critical evaluation, and educational conditions. AI chatbots may appeal for immediate and personalized help, but they usually do not offer reliable information, authentic interaction, contextual sensitivity, or clear rules of authorship. Consequently, the study advocates careful, transparent, contextualized integration of AI to enhance learning, not replace judgment, expertise, or social communication. The eight constructs of the expanded TAM framework help describe acceptance and the meeting of judgments and constraints. The study did not specifically test causal pathways but offered insight into construct profiles, cross-country differences, and contextual links, not confirmation of a causal TAM sequence.

These conclusions are limited by many factors. First, the cross-sectional design measures acceptance, frequency of use, and prior experience at one time, so the time order is unclear. The strong relationship between frequency and acceptance may be the result of learning, self-selection, or reciprocity. The statistical results should be regarded as associations. Furthermore, self-reported quantitative figures often do not align with perceived usefulness, behavioral intention, actual use, or system logs. The third limitation of generalizability is due to convenience and snowball recruitment. Students of English as a Foreign Language (EFL) at university who agreed to take part in the research and were reachable online may have been more interested and/or had better access and/or more digital experience compared to other university EFL learners.

The study's findings support using the chatbot as a flexible language-learning tool. Learners appreciated explanatory strategies, error correction, translation, examples, vocabulary and grammar practice, writing support, and repetition of the same question. Teachers can strengthen these by asking students to compare AI responses with course sources, identify and correct errors, justify accepted suggestions, revise the prompt, or produce an independent text after weighing options. These tasks use chatbots to support students, strengthening their reasoning, linguistic choices, and revision.

Verification needs to be included in classroom practices. Students must have practical ways to verify the correctness of grammatical explanations, facts, examples/references in dictionaries/corpora/course materials, credible sources, and teacher feedback. They must understand that fluent words can also be inaccurate or inappropriate in some contexts. Attribution checking needs to be practiced when using EFL activities, since reliability issues arose in both camps, not just as a warning against AI in general.

Instruction should also accommodate differing prior experience. Inexperienced users may not know how to define a task, ask for an appropriate level of expertise, refine a prompt, grade a response, safeguard private data, or tell the difference between real help and submitting work. More experienced learners might already use those strategies. A brief, guided onboarding

minimizes common procedures without assuming access to the same application provides equal opportunity. The mere correlation between experience and acceptance does not mean training will change your perspective. Consequently, institutions would benefit from assessing the effect of onboarding on judgment, trust calibration, and learning behavior.

Future studies should check whether the extended TAM tool works consistently across languages and settings. It would be advisable to conduct cognitive interviews to explore learners' interpretations of items and document translation procedures to ensure semantic equivalence. Confirmatory factor analysis, along with invariance tests, has been employed to study construct relationships and means. Furthermore, future research should specify and compare text-only, voice-enabled, general-purpose, EFL-specific, free, paid, and transparent systems, as these may affect acceptance and learning.

Bio-data

First Author: is a Ph.D. candidate in the Department of English Language and Literature, Razi University, Kermanshah. She is interested in conducting research in CALL. She has also given presentations at national conferences.

Second Author: a professor of applied linguistics in the Department of English Language and Literature, Razi University, Kermanshah. He is interested in conducting research in CALL, MALL, dynamic assessment, Artificial intelligence, and SLA. He has published in many distinguished national and international journals. He has also given presentations at national and international conferences.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interest: The authors declare that they have no competing interests.

References

AbuSahyon, A. (2023). Investigating the impact of AI-driven chatbots on the acquisition of English as a foreign language among Saudi undergraduate students. International Journal of Membrane Science and Technology, 10(2), 3075-3088. https://doi.org/10.15379/ijmst.v10i2.3049

Alotumi, M. (2022). Factors influencing graduate students' behavioral intention to use Google Classroom: Case study-mixed methods research. Education and Information Technologies, 27(7), 10035-10063.

Alshare, K., Mesak, H., Grandón, E., & Badri, M. (2011). Examining the moderating role of national culture on an extended technology acceptance model. Journal of Global Information Technology Management, 14(3), 27-53. https://doi.org/10.1080/1097198x.2011.10856542

Athanassopoulos, S. (2023). The use of ChatGPT as a learning tool to improve foreign language writing in a multilingual and multicultural classroom. Advances in Mobile Learning Educational Research, 3(2), 818-824. https://doi.org/10.25082/amler.2023.02.009

Belda-Medina, J., & Calvo-Ferrer, J. R. (2022). Using chatbots as AI conversational partners in language learning. Applied Sciences, 12(17), 8427. https://doi.org/10.3390/app12178427

Creswell, J. W., & Plano Clark, V. L. (2018). Designing and conducting mixed methods research (3rd ed.). Sage.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Derakhshan, A., & Ghiasvand, F. (2024). Is ChatGPT an evil or an angel for second language education and research? A phenomenographic study of research-active EFL teachers' perceptions. International Journal of Applied Linguistics. https://doi.org/10.1111/ijal.12561

Dörnyei, Z. (2007). Research methods in applied linguistics. Oxford University Press.

Elshaer, I. A., Hasanein, A. M., & Sobaih, A. E. E. (2024). The moderating effects of gender and study discipline in the relationship between university students' acceptance and use of ChatGPT. European Journal of Investigation in Health, Psychology and Education, 14(7), 1981–1995. https://doi.org/10.3390/ejihpe14070132

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. British Journal of Educational Technology, 50(5), 2572–2593. https://doi.org/10.1111/bjet.12864

Hwang, M., Lee, E., & Lee, H. K. (2025). Exploring EFL learners' acceptance of ChatGPT: Application of the extended technology acceptance model. English Teaching, 80(1), 45–69. https://doi.org/10.15858/engtea.80.1.202503.45

Kohnke, L., Moorhouse, B. L., & Zou, D. (2023). ChatGPT for language teaching and learning. RELC Journal, 54(2), 537–550. https://doi.org/10.1177/00336882231162868

Kucuk, T. (2024). ChatGPT integrated grammar teaching and learning in EFL classes: A study on Tishk International University students in Erbil, Iraq. Arab World English Journal, 100-111.

Liu, G., & Ma, C. (2024). Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model. Innovation in Language Learning and Teaching, 18(2), 125–138. https://doi.org/10.1080/17501229.2023.2240316

Ma, D., Akram, H., & Chen, I. H. (2024). Artificial intelligence in higher education: A cross-cultural examination of students' behavioral intentions and attitudes. International Review of Research in Open and Distributed Learning, 25(3), 134-157.

Panagiotarou, A., Stamatiou, Y. C., Pierrakeas, C., & Kameas, A. (2020). Gamification acceptance for learners with different e-skills. International Journal of Learning, Teaching and Educational Research, 19(2), 263-278. https://doi.org/10.26803/ijlter.19.2.16

Punar Özçelik, N., & Yangın Ekşi, G. (2024). Cultivating writing skills: The role of ChatGPT as a learning assistant—a case study. Smart Learning Environments, 11(1), 10. https://doi.org/10.1186/s40561-024-00296-1

Sallam, M., Elsayed, W., Al-Shorbagy, M., Barakat, M., El Khatib, S., Ghach, W., Alwan, N., Hallit, S., & Malaeb, D. (2024). ChatGPT usage and attitudes are driven by perceptions of usefulness, ease of use, risks, and psychosocial impact: A study among university students in the UAE. Frontiers in Education, 9, 1414758. https://doi.org/10.3389/feduc.2024.1414758

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Wong, L. (2024). From hype to insight: Exploring ChatGPT's early footprint in education via altmetrics and bibliometrics. Journal of Computer Assisted Learning, 40(4), 1428-1446. https://doi.org/10.1111/jcal.12962

Xiao, Y., & Zhi, Y. (2023). An exploratory study of EFL learners' use of ChatGPT for language learning tasks: Experience and perceptions. Languages, 8(3), 212. https://doi.org/10.3390/languages8030212

Zou, B., Lyu, Q., Han, Y., Li, Z., & Zhang, W. (2023). Exploring students' acceptance of an artificial intelligence speech evaluation program for EFL speaking practice: An application of the integrated model of technology acceptance. Computer Assisted Language Learning. https://doi.org/10.1080/09588221.2023.2278608