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Predictors of ChatGPT Acceptance in Language Education: A Study of Pre-Service ELT Students in Uzbekistan Author Names and Affiliations

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Abstract

The integration of artificial intelligence applications, such as Google's Little Language Labs and ChatGPT, is accelerating, with language education representing a particularly prominent domain of adoption. As future practitioners, pre-service English Language Teaching (ELT) students play a pivotal role in determining how these technologies are implemented in instructional settings. This study investigates their acceptance of ChatGPT within the framework of the Unified Theory of Acceptance and Use of Technology (UTAUT2), a model that has rapidly gained substantial scholarly recognition since its introduction. Employing a cross-sectional survey design, data were collected in May 2025 from 456 pre-service ELT students enrolled at universities across Uzbekistan through an anonymous online questionnaire administered via Google Forms. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with a weighting path scheme in SmartPLS 4. The results indicate that habit, performance expectancy, effort expectancy, and personal innovativeness have significant positive effects on behavioral intention to use ChatGPT. By contrast, social influence, facilitating conditions, and hedonic motivation did not significantly predict behavioral intention. Furthermore, facilitating conditions, habit, and behavioral intention did not significantly influence actual use behavior. Gender and year of study were tested as moderating variables; however, neither demonstrated a significant moderating effect. These findings highlight the central importance of habit, performance expectancy, effort expectancy, and personal innovativeness in shaping pre-service ELT students' intentions to adopt ChatGPT, while other UTAUT2 constructs appear less influential in this context. Notably, this is the first study to apply the UTAUT2 framework to examine ChatGPT acceptance among pre-service ELT students in Uzbekistan. Future research should extend this line of inquiry by including broader samples across universities and regions, thereby enabling more comprehensive insights into technology acceptance following cultural adaptation of the UTAUT2 framework in underexplored regions.

Introduction

In today's rapidly developing world, it is difficult to imagine modern life without technology and the advancement of technological tools. These developments are not only a way for shaping modern life but it can also be a reason for further discussions about it, mostly about the introduction and usage of artificial intelligence (P. Wang, 2019). Artificial intelligence (AI) is being recognized as a core part of the ongoing expansion in digitally driven society, which is influencing all fields of life (Cooper, 2023). One of the domains of the integration of AI is the educational institutions where technological tools are applied to acquire foreign languages and teach them effectively. A notable example is the introduction of ChatGPT, an AI powered Chatbot. The technology was introduced in 2022 by promoting the use of free accounts on the platform of OpenAI (OpenAI, 2023).

AI refers to human-created systems that imitate human behavior. These machines, developed through human effort, are capable of generating responses based on conventional human patterns by selecting from a wide range of internal data. Platforms like ChatGPT has a huge extensive databases that are

beneficial to be used for by foreign language learners, especially Foreign Language teaching pre-service teachers, including the functions of asking questions, generating texts, providing sources, or converting an oral information to written one (Shubhendu & Vijay, 2013). In particular, a possible use of ChatGPT is within the domain of higher education that can be through applying the tool to enhance learners' knowledge in their field. This can be used to improve students' critical thinking, academic writing as opposed to only for assessing students' performance by applying the software (Strzelecki, 2023).

The demand for learning English is increasing in Uzbekistan, making it one of the most highly demanded foreign languages in the country. People who are learning foreign languages in the country are using technological tools more effectively than before, and tools-especially AI- transforming the field of education in teaching and learning English language (Shikina, 2025). In 2024, social media influencers widely introduced ChatGPT as a conversational chatbot in the country. Its popularity surged not only among the influencers but also among educators, researchers, and pre-service teachers in higher education, particularly those specializing in foreign language instruction at state universities throughout the Republic of Uzbekistan.

While different scholars have explored the educational implications of ChatGPT (Lund & Wang, 2023), others have increasingly focused on its influence in fields like academic research and writing (Perkins, 2023). On a global scale, research on the integration of ChatGPT into teacher trainings and language education is steadily growing. Although a significant portion of this work is still undergoing peer review, it reflects a rising awareness of the tool's potential in educational contexts. The ongoing implementation of ChatGPT in higher education demonstrates that its effectiveness and pedagogical value are still under critical examination (Strzelecki, 2023). Despite the growing international interest, there remains a noticeable gap in research specifically addressing how pre-service teachers in Uzbekistan perceive, engage with, and apply ChatGPT in their academic routines.

Although numerous academic studies in the field have focused on the view and research findings of scholars and researchers, the primary stakeholders remain pre-service teachers (Strzelecki, 2023). In the context of Uzbekistan, AI tools are not only relatively new, but the field itself remains underexplored in academic discourse. There is a noticeable lack of comprehensive research and published scholarly work, indicating that the integration of AI into the education is still in its early and emerging stages. As a direct result of the current circumstances, we have proposed conducting research on how students accept and adopt ChatGPT technology. In order to assess the acceptance of technology, we utilized elements from a widely recognized framework "Unified Theory of Acceptance and Use of Technology (UTAUT2)" (Venkatesh et al., 2012).

In order to contextualize the study within Uzbekistan, a structured survey was distributed among pre-service English language teachers who are studying at state universities in Uzbekistan. The aim was to evaluate their acceptance of ChatGPT and to explore their behavioral patterns in utilizing the tool for academic purposes.

Literature Review

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

As technology continues to advance rapidly and influence various areas of our lives, it has become increasingly important to understand how users accept and adopt new innovations. Key models like the Innovation Diffusion Theory (IDT), Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) provide valuable frameworks for examining technology adoption (Xue et al., 2024). Among these, UTAUT stands out due to its incorporation of crucial elements from earlier models and its widespread application in the field of higher education research. The UTAUT and its extensions, particularly UTAUT2, have been extensively employed across diverse fields, demonstrating their robustness in predicting technology adoption and usage (Venkatesh et al., 2016). Initially formulated by Venkatesh et al. (Venkatesh et al., 2016), UTAUT synthesized constructs from different technology acceptance models (Xue et al., 2024). This foundational model identified social influence, performance expectancy, effort expectancy, and facilitating conditions as direct determinants of user acceptance and use behavior (Xue et al., 2024). Specifically, performance expectancy reflects the degree to which an individual believes that using a system will contribute to improved job performance, whereas effort expectancy captures the perceived ease of use associated with the system (Xue et al., 2024). Social influence encompasses the degree to which an individual perceives that important others believe they should use the technology, and facilitating conditions pertain to the availability of technical and organizational infrastructure supporting system use (Alqahtani & Braun, 2021). The initial UTAUT framework accounted for nearly 70% of the variance in individuals' behavioral intentions and roughly 50% of the variance in their actual use of technology (Tamilmani et al., 2021). However, to enhance its applicability in consumer contexts, Venkatesh et al. later introduced UTAUT2, which incorporated additional constructs such as hedonic motivation, price value, and habit, thus extending its explanatory power to encompass a broader spectrum of user motivations (Amnas et al., 2023). The inclusion of hedonic motivation, price value, and habit in UTAUT2 addressed specific gaps in the original UTAUT model, which was primarily organizational in scope, by acknowledging the intrinsic and extrinsic factors driving consumer technology adoption (Tamilmani et al., 2021) In 2023, Strzelecki (2023) has adopted UTAUT2 to determine university students' acceptance and use of ChatGPT and price value has been omitted in this context as ChatGPT is free and since then, various researchers used this model to identify the ChatGPT's acceptance and use among different groups (Faraon et al., 2025; Grassini et al., 2024). Likewise, our study adopted UTAUT2 to determine ChatGPT acceptance and use among university students in Uzbekistan.

Performance expectancy

The concept of performance expectancy is provided as users' beliefs of how technological tools and systems maximize their work and task performance based on their expectations (Davis, 1989; Venkatesh et al., 2003) Performance expectancy in the context of ChatGPT, refers to the user's belief that employing the AI tool will enhance the efficiency and effectiveness of their tasks, thereby contributing to their productivity (Felber et al., 2024). This factor is significant, as users who believe that ChatGPT enables them to accomplish their objectives more efficiently are more inclined to adopt and incorporate it into their daily practices (Kelly et al., 2022). Various studies have demonstrated that performance expectancy is a significant predictor of behavioral intention across numerous technological adoptions, including generative AI tools (Cortez et al., 2024; Faraon et al., 2025; Grassini et al., 2024; Habibi et al., 2024). Accordingly, our first hypothesis was:

H1. Performance expectancy will have a significant direct influence on behavioral intention.

Effort expectancy

The perceived simplicity of using a technology, known as effort expectancy, has a notable impact on individuals' intention to use it, particularly in educational contexts involving AI applications (Wang et al., 2024). This concept is essential in higher education where the extensive use of ChatGPT and similar technologies calls for awareness of how students perceive the effort required for learning, interacting with, and applying such technologies in their academic pursuits (Chan & Zhou, 2023). Empirical evidence indicates that students' perceptions of simplicity and low effort in using AI applications play a positive role in shaping their willingness to adopt them (Faraon, et al., 2025; Khlaif et al., 2024). Specifically, students who consider generative AI user-friendly are more likely to incorporate it into their regular academic activities, thereby increasing its overall utility and adoption (Menon & Shilpa, 2023). This is particularly evident in studies examining the UTAUT in educational settings, where effort expectancy consistently emerges as a significant predictor of students' willingness to engage with generative AI (Baharin, 2025). These results are further reinforced by evidence showing a significant positive relationship between students' perceived benefits of generative AI and their intention to adopt it, suggesting that ease of use enhances this perceived value (Chan & Zhou, 2023). This influence is evident in various contexts, from mobile learning applications to AI-driven diagnostic support systems, where a lower perceived effort generally correlates with a higher propensity for adoption and sustained use (Wang et al., 2024). Accordingly, the our second hypothesis in this study was:

H2. Effort expectancy will have a significant direct influence on behavioral intention.

Social influence

Social influence, a pivotal construct within the UTAUT2, profoundly shapes individuals' behavioral intentions and subsequent technology adoption (Graf-Vlachy et al., 2018; Joa & Magsamen-Conrad, 2021). This influence stems from an individual's perception that important others believe they should

use a particular technology (Eckhardt et al., 2009). Specifically, this encompasses the perceived pressure from social networks, including family, friends, and peers, which can significantly sway an individual's decision-making process regarding technology usage (Yang et al., 2022). This construct has been shown to predict perceived usefulness, ultimately influencing continuance intention toward various applications (Li et al., 2022). In education, social influence is particularly salient, as students' technology adoption can be heavily mediated by the expectations and behaviors of their peers and instructors (Sergeeva et al., 2025). Accordingly our third hypothesis was: .

H3. Social influence will have a significant direct influence on behavioral intention.

Facilitating conditions

Facilitating conditions are defined as the degree of organizational and technical infrastructure present to support the use of a system (Kelly et al., 2022). This can include technical support, resources, and knowledge required for individuals to effectively utilize a technology (Almenara et al., 2025; Baharin, 2025). This structural support mitigates perceived barriers to adoption and use by ensuring users possess the requisite resources and knowledge for successful engagement (Rana et al., 2024). Accordingly, our fourth and fifth hypotheses were:

H4 & H5: Facilitating conditions will have a significant direct influence on behavioral intention and use behavior.

Hedonic motivation

Experiencing pleasure or enjoyment from using a technology, known as hedonic motivation, is also an important factor affecting behavioral intention, especially regarding the adoption of AI applications (Cabrera-Sánchez et al., 2020). The inherent appeal and satisfaction experienced during interaction with AI tools can thus significantly boost an individual's willingness to adopt and consistently utilize these technologies (Baig & Yadegaridehkordi, 2025). This enjoyment factor, distinct from purely utilitarian considerations, often drives sustained engagement and deeper integration of new technologies into daily practices. Accordingly, our sixth hypothesis was:

H6: Hedonic motivation will have a significant direct influence on behavioral intention.

Habit

Habit, characterized by automated behaviors resulting from repeated past actions, also impacts the continued intention to use AI applications (Yu et al., 2024). Various studies indicate habit as the strongest predictor of behavioral intention (Azizi et al., 2020; Al-Azawei & Alowayr, 2020; Moorthy et al., 2019; Nikolopoulou et al., 2020; Twum et al., 2022; Zwain, 2019). Consequently, a strong habit formed around AI tool usage can lead to consistent engagement, even in the absence of conscious deliberation,

highlighting its profound effect on long-term adoption (Gajić et al., 2024). Also, habit was found to have a direct impact on use behavior (García et al., 2025; Strzelecki, 2023). Accordingly, our seventh and eight hypotheses were:

H7&H8: Habit will have a significant direct influence on behavioral intention and use behavior.

Personal innovativeness

Personal innovativeness refers to the extent to which a person is open to experimenting with new information technologies (Biswas et al., 2025). Various studies found that personal innovativeness impacts behavioral intention (Biswas et al., 2025; Twum et al., 2022). Accordingly, our ninth hypothesis was:

H9: Personal innovativeness will have a significant direct influence on behavioral intention.

Behavioral intention

Behavioral intention reflects a person's perceived likelihood of performing a particular action and serves as an immediate predictor of actual technology use (Yi & Choi, 2023). In contrast, use behavior pertains to the real-world utilization of the technology, which is the ultimate outcome predicted by the UTAUT2 model (Kim et al., 2024). In this framework, behavioral intention acts as a direct antecedent to actual use, encompassing the user's conscious decision and plan to engage with the technology (Amnas et al., 2023). Accordingly, our tenth hypothesis was:

H10: Behavioral intention will have a significant direct influence on use behavior.

As in other studies on the acceptance and use of ChatGPT, we looked into the moderating/mediating effect of study year and gender on the construct of this model and formed the following hypotheses:

H11: Study year and gender will have a moderating/ mediating effect on the impact of habits on BI and use behavior.

H12: Study year and gender will have a moderating/ mediating effect on the impact of hedonic motivation on behavioral intention.

H13: Study year and gender have a moderating/ mediating effect on the impact of facilitating conditions on behavioral intention and use behavior.

Method

This research employed a cross-sectional survey design and was carried out in Uzbekistan in June 2025. Following approval from the institutional ethics committee, pre-service ELT students from multiple

universities were invited to participate. The questionnaire was completed anonymously, and the primary aim was to capture students' perspectives on the use of ChatGPT.

Participants and procedure

Participants of the current study were 456 pre-service ELT department freshmen, sophomores, juniors, and senior year students from different universities in Uzbekistan who will be working as English language teachers after their studies. They completed the online survey distributed through Google Forms in May 2025. Of the 456 respondents, 390 were female, 55 were male and 11 indicated that they were not willing to disclose. Of those 456 participants, 155 were first-year students, 71 were second-year students, 169 were third-year students and 61 were fourth-year students.

Data Collection Tool

The present study employed the UTAUT2 framework developed by Venkatesh et al. (2012), which was later adapted by Strzelecki (2023) to examine the adoption and use of ChatGPT. This model was applied to investigate pre-service ELT teachers' acceptance and utilization of ChatGPT in Uzbekistan. UTAUT2 incorporates six predictors from the original UTAUT, performance expectancy, facilitating conditions, effort expectancy, hedonic motivation, social influence, and habit, along with an additional construct, personal innovativeness. Items corresponding to each construct were measured using a five-point Likert scale ranging from strongly agree to strongly disagree. Consistent with Strzelecki's (2023) approach, use behavior was assessed through a seven-point frequency scale ranging from never to several times per day.

Results

The model was evaluated using the PLS-SEM algorithm in SmartPLS 4 software. The constructs were assessed based on their indicator loadings. An indicator's reliability is considered satisfactory if its loading is greater than 0.70, indicating that the construct accounts for more than 50% of the variance in the indicator (Chin, 1998; Hair et al., 2011). The loadings for each item are presented in Table 1 below.

Table 1
Included scale items, and factor loadings.

Construct	Item	Loading	Mean	St dev.
Performance expectancy	PE1	0.780	3.86	0.785
	PE2	0.812	3.59	0.928
	PE3	0.714	3.97	0.792
	PE4	0.782	3.52	0.960
Effort expectancy	EE1	0.750	3.93	0.841
	EE2	0.755	3.79	0.812
	EE3	0.733	4.01	0.783
	EE4	0.800	3.62	0.964
Social influence	SI1	0.870	3.15	1.001
	SI2	0.866	2.98	0.983
	SI3	0.878	3.16	0.964
Facilitating conditions	FC1	0.828	3.51	0.891
	FC2	0.809	3.52	0.901
	FC3	0.793	3.61	0.824
Hedonic motivation	HM1	0.830	3.67	0.909
	HM2	0.915	3.68	0.899
	HM3	0.889	3.59	0.974
Habit	HT1	0.830	3.32	1.024
	HT2	0.775	2.95	1.051
	HT3	0.809	2.90	1.008
	HT4	0.839	3.26	0.938
Behavioral intention	BI1	0.849	3.41	0.967
	BI2	0.862	3.35	0.980
	BI3	0.856	3.29	0.974
Personal innovativeness	PI1	0.748	3.73	0.845
	PI2	0.789	3.57	0.856
	PI3	0.786	3.54	0.979

Construct	Item	Loading	Mean	St dev.
	PI4	0.805	3.55	0.921
Use behavior	UB1	1.000	5.14	1.674

The internal consistency reliability was examined using Cronbach's alpha. Convergent validity was assessed using the average variance extracted (AVE), where values of 0.50 or above were deemed satisfactory (Sarstedt et al., 2021). All indicators, including Cronbach's alpha, composite reliability, the reliability coefficient, and AVE, satisfied the predetermined quality standards, as detailed in Table 2.

Table 2
Construct reliability and validity

	Cronbach's alpha	Reliability coefficient	Composite reliability	AVE
Behavioral intention	0,817	0,817	0,891	0,732
Effort expectancy	0,760	0,779	0,845	0,578
Facilitating conditions	0,738	0,740	0,851	0,656
Habit	0,831	0,842	0,887	0,662
Hedonic motivation	0,853	0,864	0,911	0,773
Performance expectancy	0,775	0,782	0,856	0,597
Personal innovativeness	0,789	0,790	0,863	0,612
Social influence	0,842	0,852	0,904	0,759

Henseler et al. (2015) advocate for the use of the heterotrait-monotrait ratio of correlations (HTMT) as a measure for assessing discriminant validity in PLS-SEM analysis. They propose a threshold of .90; values exceeding this threshold signal a deficiency in discriminant validity. As demonstrated in Table 3, all HTMT values fall below .90, indicating robust discriminant validity among the constructs.

Table 3
Htmt values

	BI	EE	FC	HT	HM	PE	PI	SI
BI								
EE	.619							
FC	.622	.734						
HT	.845	.538	.616					
HM	.633	.733	.659	.621				
PE	.698	.777	.713	.642	.652			
PI	.596	.479	.635	.494	.609	.512		
SI	.648	.524	.712	.726	.544	.662	.397	
UB	.162	.140	.160	.187	.143	.232	.123	.017

BI: Behavioral intention; EE: effort expectancy; FC: Facilitating conditions; HT: habit; HM: hedonic motivation; PE: performance expectancy; PI: personal innovativeness; SI: Social influence; UB: use behavior; ET: ethical attitude.

The PLS-SEM analysis results are shown in Fig. 1. It is indicated that R^2 measures are one of the primary criteria in structural model evaluation, and higher R^2 indicates larger explanatory power (Hair et al. 2011). R^2 values of 0.75, 0.50, and 0.20 are considered substantial, moderate, and weak, respectively (Sarstedt et al., 2021). The R^2 value for behavioral intention in this model, as given inside the circle, was .603, indicating a moderate level of explained variance, which suggests that the model accounts for a considerable portion of variance in this construct. On the other hand, the R^2 value for use behavior was .042, which falls below the threshold for weak explanatory power, indicating that the model explains only a small fraction of variance in this construct.

As for the effect size, the f^2 values of 0.02, 0.15, and 0.35 indicate a predictor's small, medium, or large effect (Hair et al., 2022). Values of f^2 smaller than 0.02, indicate no impact (Sarstedt et al., 2021). As seen in Fig. 1, the analysis shows that the statistically significant determinants of "behavioral intention" were "habit" (.456), "personal innovativeness" (.183), "performance expectancy" (.128), and "effort expectancy" (.102). The other factors, "social influence" (.082), "facilitating conditions" (.020), "hedonic motivation" (.084) also had a positive effect on "behavioral intention", however, the f2 effect size was not significant. Additionally, facilitating conditions, behavioral intention and habit did not have a significant impact on use behavior.

Table 4. Path coefficients and significance testing

Hypothesis	Path		Coefficient	P value	F2	Confirmed
H1	Performance expectancy	→ Behavioral intention	.128	.006	.020	Yes
H2	Effort expectancy	→ Behavioral intention	.102	.024	.013	Yes
H3	Social influence	→ Behavioral intention	.082	.079	.008	No
H4	Facilitating conditions	→ Behavioral intention	-.020	.693	.000	No
H5	Facilitating conditions	→ Use behavior	.075	.175	.004	No
H6	Hedonic motivation	→ Behavioral intention	.084	.363	.004	No
H7	Habit	→ Behavioral intention	.456	.000	.156	Yes
H8	Habit	→ Use behavior	.120	.201	.004	No
H9	Personal innovativeness	→ Behavioral intention	.163	.000	.044	Yes
H10	Behavioral intention	→ Use behavior	.016	.813	.000	No

The model incorporated "gender" and "study year" as mediating factors, and the findings regarding their mediating influence indicated that neither gender nor study year had a notable effect.

Discussion & Conclusion

This study aimed to identify the predictors of the UTAUT2 model that influence pre-service ELT students' acceptance and use of ChatGPT in Uzbekistan. The study builds on previous research regarding ChatGPT, which has primarily focused on Western countries (Faraon et al., 2025; Nikolopoulou et al., 2021; Nikolopoulou et al., 2020; Strzelecki, 2023), and presents the first investigation in Uzbekistan into higher education students and prospective EFL teachers using the UTAUT2 model.

The results of this study offer important insights. The results of PLS-SEM indicated that among the UTAUT2 predictors adapted to ChatGPT by Strzelecki (2023), habit, performance expectancy, effort expectancy and personal innovativeness were found to have a significant positive impact on behavioral intention. That performance expectancy had a significant direct impact on behavioral intention supported our H1; while the finding that effort expectancy, habit and personal innovatiness had a significant direct impact on behavioral intention supported our H2, H7 and H9, respectively. Particularly, habit was the strongest predictor of behavioral intention. This finding aligns with other studies (Grassini et al., 2024; Moorthy et al., 2019; Nikolopoulou et al., 2021; Osei et al., 2022; Strzelecki, 2023; Zheng et al. 2025). On the other hand, the hypotheses that social influence (H3), facilitating conditions (H4) and hedonic motivation (H6) had a direct and significant impact on behavioral intention were rejected, as were H5, H8 and H10 which posited significant impact of facilitating conditions, habit and behavioral intention on use behavior. Furthermore, there was no moderating or mediating effect of gender or study year on behavioral intention and use behavior, nor on the impact of hedonic motivation on behavioral intention and the effect of facilitating conditions on both behavioral intention and use behavior.

Looking into the details, habit emerged as the strongest predictor of behavioral intention. This suggests that students who have developed routines or familiarity with using digital tools, such as ChatGPT, are more likely to continue using them. When learners regularly interact with digital tools like ChatGPT, their utilization becomes a habitual reaction prompted by particular situations such as getting academic support with tasks. This way, habit minimizes the mental effort needed to select a tool, making ongoing usage nearly automatic and strengthening commitment. This finding is consistent with previous studies (Moorthy et al., 2019; Nikolopoulou et al., 2021; Osei et al., 2022; Strzelecki, 2023; Zheng et al. 2025),

which indicate that habitual usage patterns significantly enhance intentions in digitally mediated learning environments. In Zheng et al.,'s (2025) meta-analysis of 91 studies looking into the key factors influencing behavioral intention to use e-learning during COVID-19 at tertiary education, they found that habit was the most influential antecedent of behavioral intention. Also, the finding that performance expectancy had a significant positive impact on behavioral intention aligns with other recent studies in the literature (Diao et al., 2024; Grassini et al., 2024; Nikolopoulou et al., 2021; Nikolopoulou et al., 2020; Patil & Undale, 2023; Raza et al., 2022; Strzelecki, 2023; Tseng et al., 2022). When students see that using ChatGPT helps them achieve better outcomes and perform tasks more effectively, they are more likely to intend to use the tool. When students recognize benefits like quicker access to information, enhanced quality of outputs, or assistance with challenging tasks, their positive expectations are likely to enhance their motivation to incorporate technology into their educational practices.

A third antecedent of behavioral intention was found to be effort expectancy. In Strzelecki's (2023) study on the acceptance and use of ChatGPT, effort expectancy was also confirmed to have a significant impact on behavioral intention. Similarly, in their study in which they looked into the impact of effort expectancy and facilitating conditions on university students' behavioral intention to use mobile learning, Aljojo & Alsuhaimi (2020) found that effort expectancy was a significant predictor of behavioral intention. The fourth predictor of behavioral intention in our study was personal innovativeness. A recent study by Tian et al. (2024) examined how graduate students in Chinese higher education accept and use AI chatbots. The findings revealed that personal innovativeness significantly affects students' intention to use AI chatbots. This highlights the importance of individual characteristics in adopting technology within higher education.

Our findings show that social influence and hedonic motivation did not significantly affect behavioral intention, which contradicts Strzelecki's (2023) findings. The insignificance of social influence suggests that students' decisions to use ChatGPT may be largely self-driven rather than shaped by other factors. Today, students often independently explore and integrate digital tools, particularly those widely accessible and user-friendly. Similarly, the lack of significance for hedonic motivation may be due to the fact that students primarily view ChatGPT as a practical, task-oriented tool rather than a source of entertainment or enjoyment. On the other hand, as in Strzelecki's (2023) study, facilitating conditions did not significantly affect behavioral intention.

As for the impact of facilitating conditions, habit and behavioral intention on use behavior, our hypotheses were rejected while in Strzelecki (2023) all three of them had a significant impact on use behavior. These contrasting findings may reflect contextual, cultural, or infrastructural differences in how AI tools like ChatGPT are introduced, accessed, and used in different regions and educational systems.

Importantly, this study makes a significant contribution to the field by being the first to apply the UTAUT2 framework to analyze ChatGPT acceptance in Uzbekistan (Xue et al., 2024) a context that has so far been underrepresented in technology acceptance literature. Most UTAUT2-based studies have been conducted in Western or East Asian contexts, meaning that cultural, pedagogical, and infrastructural

factors unique to Central Asia remain largely unexplored. As AI tools become more globally embedded in education, understanding how pre-service teachers in diverse and non-Western contexts perceive and adopt these tools is essential. By focusing on Uzbekistan, this study offers valuable insights for other post-Soviet, transitional, and developing education systems facing similar challenges of balancing tradition and digital transformation. The findings contribute to a more nuanced understanding of how cultural and contextual factors moderate the relationships proposed in UTAUT2, helping policymakers, teacher educators, and technology developers design more context-sensitive strategies for AI integration. In doing so, this research not only fills a geographical gap in the literature but also extends the applicability and validity of UTAUT2 to underexplored educational contexts.

Moreover, pre-service ELT students, as future implementers of classroom technology, play a pivotal role in determining how effectively AI tools are integrated into language education. By focusing on this demographic, the study not only highlights the current state of readiness among future teachers but also informs curriculum developers and policymakers about the types of support, pedagogical, motivational etc., that should be prioritized in teacher education programs. Understanding pre-service teachers' attitudes is especially important because they represent a generation of educators who will bridge traditional teaching practices with emerging digital pedagogies. Their experiences with AI during teacher education programs can either facilitate a smooth transition into technology-rich classrooms or reinforce resistance to innovation. By identifying gaps, this research can guide the development of comprehensive teacher education curricula.

Ultimately, by focusing on pre-service ELT students in a rapidly evolving educational context, this study provides strategic insights for policy and program design. Investments in teacher education programs that combine technical training, pedagogical guidance, and motivation-building strategies are essential for scaling up AI integration effectively, particularly in countries navigating the balance between traditional educational values and digital transformation.

In summary, this study provides unique insights into the acceptance and utilization of ChatGPT among pre-service ELT students in Uzbekistan using the UTAUT2 framework. The findings demonstrate that performance expectancy, effort expectancy, habit and personal innovativeness significantly influence behavioral intention, highlighting the critical role of individual perceptions and usage behaviors in the adoption of technology. Conversely, the study reveals that social influence, facilitating conditions, and hedonic motivation did not have significant effects, nor did gender and year of study serve as moderating or mediating factors. As the first investigation of its kind within the Uzbek context, these results enrich the existing literature on AI acceptance in education and underscore the necessity for customized support mechanisms that extend beyond mere infrastructure and encompass pedagogical and motivational aspects in teacher training.

Limitations and suggestions

Despite its contributions, this study has limitations as well. First, the sample was limited to pre-service ELT students from one region and selected institutions in Uzbekistan, which may affect the generalizability of the findings to other disciplines or regions. Another limitation is that the participants of the current study were mainly female. Future research could employ a balanced number of male and female participants for a better representation of both genders.

Also, since UTAUT2 provides a strong theoretical basis, future research could be expanded to include diverse disciplines and institutions in Uzbekistan to enhance the generalizability of the findings. Additionally, future studies may also consider extending the UTAUT2 model with culturally relevant variables or pedagogical beliefs to better capture the complexities of AI adoption in diverse educational settings. To do so, cultural adaptation of UTAUT2 into Uzbek language enabling other research areas to look into the factors effecting acceptance and use of ChatGPT as well as other AI tools could be an essential step for future research and thus, more data shall be available from the region.

Declarations

Funding and Conflict of Interest

The authors state that they have no financial support or competing interests concerning the material presented in this article.

Contribution

All authors contributed to the study design. The initial version of the manuscript was prepared collectively, and each author reviewed and approved the final manuscript.

Data Accessibility Statement

The datasets of this study can be obtained from the corresponding author upon a reasonable request.

Ethics & Consent to Participate

The study adhered to the ethical standards set forth by the Declaration of Helsinki. Ethical approval was granted by the ethics committee at Bartın University (Decision No: 2025-SBB-0555). No personal identifying details were gathered from the participants.

Before participating in the survey, individuals were provided with comprehensive information about the study's aims. Their informed consent was acquired prior to completing the survey, and they were guaranteed the option to withdraw from the study at any point.

Clinical trial number: not applicable.

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Figures

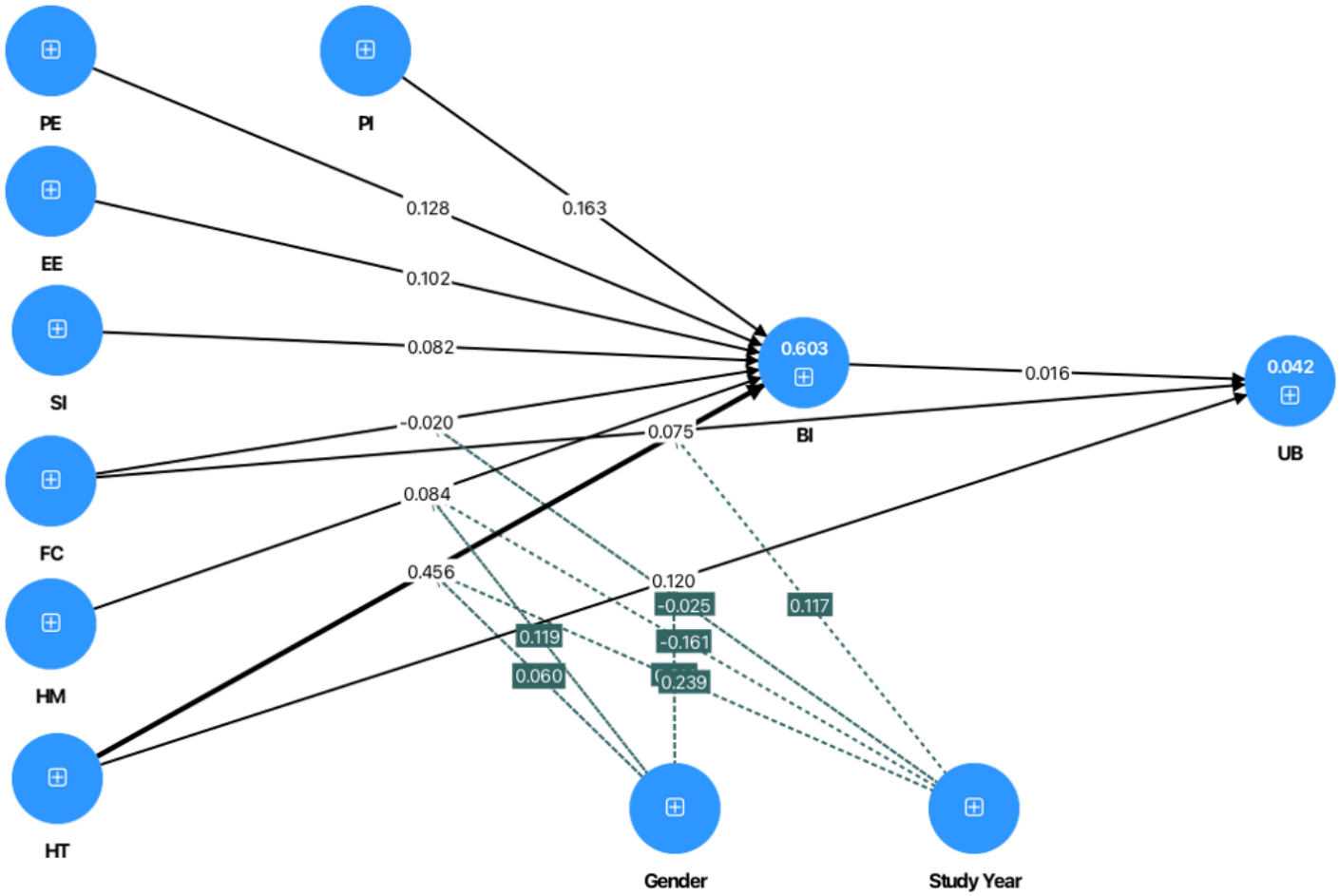

Figure 1

Results from UTAUT2 on the predictors of acceptance and use of ChatGPT among pre-service ELT students