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UNDERSTANDING STUDENT ADOPTION OF GENERATIVE AI CHATBOTS IN HIGHER EDUCATION: AN INTEGRATED TAM–TRI APPROACH

Samalgul Nassanbekova[1], Gaukhar Yeshenkulova[1*], Assel Nurguzhina[2], Mohamed Ibrahim[2], Nurkhat Ibadildin[1]

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[1] Astana IT University, School of Digital Public Administration, Kazakhstan

[2] Astana IT University, School of Creative Industries, Kazakhstan

[*]Corresponding Author:
Gaukhar Yeshenkulova

Email:
gaukhar.yeshenkulova@astanait.edu.kz

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ABSTRACT

The rapid integration of generative artificial intelligence (AI) in education has created a growing need to understand the factors that shape students' adoption of these technologies. This study examines the behavioural, cognitive, and ethical determinants of AI chatbot use among university students. Drawing on the Technology Acceptance Model and the Technology Readiness Index, the study incorporates additional constructs, including transparency and ethics. Data were collected through an online questionnaire administered to 285 students and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings indicate that optimism significantly influences perceived ease of use, which, together with perceived usefulness and transparency/ethics, positively affects students' intention to use AI chatbots. Transparency/ethics also exerts a direct effect on actual usage behaviour, underscoring the increasing importance of trust and responsible AI in educational contexts. The study provides both theoretical and practical implications for developers, educators, and policymakers seeking to encourage meaningful and responsible AI adoption in higher education.

Keywords: *AI chatbot adoption, generative AI, Technology Acceptance Model, Technology Readiness Index transparency, AI ethics, PLS-SEM*

1. INTRODUCTION

The integration of generative AI chatbots, such as ChatGPT and Gemini, is transforming higher education by providing personalized support, improving student engagement, and streamlining administrative tasks. As these tools become more prevalent, students must adapt to rapidly evolving digital learning environments. Understanding the factors that shape the acceptance and effective use of AI chatbots has therefore become increasingly important. Technology adoption in education is influenced by multiple factors and has often been examined through the Technology Acceptance Model (TAM), introduced by Davis (1989), which identifies perceived ease of use (PEU) and perceived usefulness (PU) as key determinants of intention to adopt new technologies. Building on TAM, later studies have proposed additional frameworks to better capture the complexity of AI adoption. For example, Foroughi et al. (2024) identified performance expectancy, effort expectancy, learning value, and hedonic motivation as important drivers of ChatGPT use intention. In parallel, Parasuraman (2000) introduced the Technology Readiness Index (TRI), which explains individuals' propensity to embrace new technologies, while Parasuraman and Colby (2015) emphasized factors such as innovativeness and optimism. More recent studies have integrated TAM and TRI in the context of large language model adoption in education and extended these models with further dimensions. Saihi et al. (2024), for instance, proposed a structural model including PEU, PU, trust, and privacy. In addition, a growing body of research highlights trust, privacy, and ethics as critical determinants of both usage intention and actual behaviour in AI-based technologies (Hasan et al., 2024; Koo et al., 2025; Rana et al., 2024; Saihi et al., 2024; C. Wang et al., 2025; Mastilo et al., 2026). Ethical concerns related to AI may substantially shape user attitudes, adoption decisions, and perceived outcomes (Du & Xie, 2021). Based on this literature, the present study combines the TAM and TRI frameworks and extends them by incorporating transparency/ethics as an additional factor expected to influence both behavioural intention and actual use of AI chatbots in education. To examine graduate students' adoption and use of AI chatbots, the study develops a comprehensive research framework and applies Partial Least Squares Structural Equation Modelling (PLS-SEM). This method is particularly suitable for analysing complex relationships among latent constructs and for assessing both direct effects and interrelationships within the model. In doing so, the study seeks to provide a more comprehensive understanding of chatbot use and perceived impact in educational settings, while addressing an important gap in the literature on LLM-based chatbots in higher education. The remainder of the paper is organized as follows. First, the theoretical background and hypothesis development are presented. Next, the methodology section describes the research design, data collection, and analytical procedures. The results section then reports descriptive statistics, reliability and validity testing, and structural model analysis. Finally, the discussion and conclusion summarize the main findings, present theoretical and practical implications, and outline the study's limitations and directions for future research.

2. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

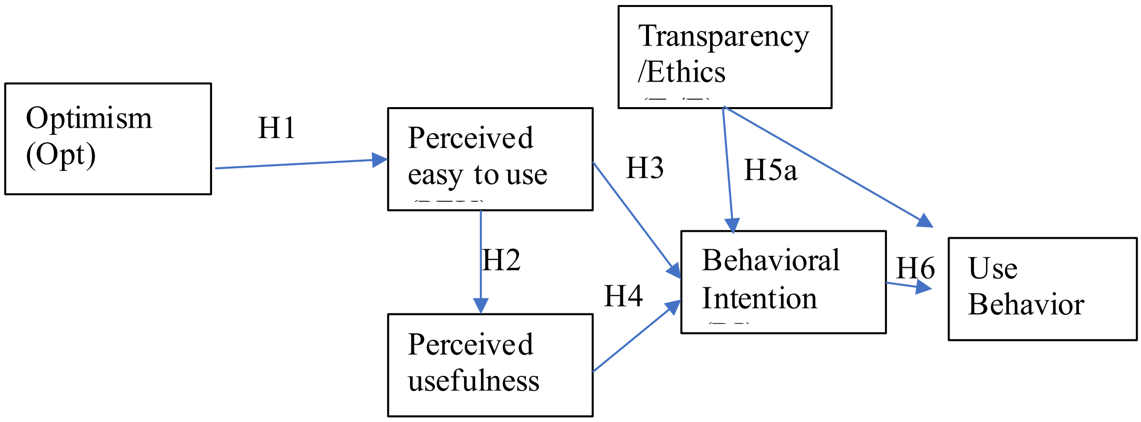
The technology acceptance model (TAM) has been widely applied to predict the acceptance of emerging technologies, including artificial intelligence (AI). Recent studies have shown that TAM constructs, particularly perceived ease of use (PEU) and perceived usefulness (PU), significantly influence user behavior toward AI-based technologies across various contexts. For example, Naidoo (2023) integrated TAM with the information systems success model and found that PU and PEU play a critical role in shaping learners' engagement with AI in education. Other extensions of TAM further demonstrate how the disruptive nature of these technologies affects user acceptance (Folkinshteyn & Lennon, 2016; Liu & Kim, 2024; Matemba et al., 2020; Pamucar et al., 2026).

Although numerous studies have employed TAM and its extensions to investigate diverse AI applications, ranging from generative AI tools such as ChatGPT to AI-based chatbots, understanding remains fragmented regarding how the core constructs interact across educational levels and cultural contexts (Acosta-Enriquez et al., 2024; Chen et al., 2024; Tang et al., 2025; Stanković and Radukić, 2026). Existing evidence suggests that performance expectancy and effort expectancy consistently predict behavioral intention, whereas the effects of social influence and facilitating conditions are sometimes found to be negligible (Nikolic et al., 2024; Obenza et al., 2024; f. Wang & Shi, 2024). This inconsistency points to an important gap in clarifying the nuanced role of TAM variables in AI acceptance.

An individual's readiness to adopt technology can be assessed using the technology readiness index (TRI), which comprises four dimensions: optimism, innovativeness, discomfort and insecurity (Parasuraman, 2000; Parasuraman & Colby, 2015). Within this framework, optimism and innovativeness function as positive drivers of technology adoption, reflecting a greater willingness to engage with new technologies, whereas discomfort and insecurity act as inhibitors that reduce technology readiness (Sohaib et al., 2020). However, more recent studies have not confirmed a significant influence of these inhibiting dimensions on the adoption of AI-based technologies (Hasan et al., 2024; Lemke et al., 2023a).

Based on this theoretical background, the present study defines the main variables of a model explaining graduate students' acceptance of AI chatbots. The model combines TAM and TRI and further incorporates transparency/ethics as an additional construct. Although innovativeness is a foundational dimension of the TRI framework, it was excluded from the final research model because of its conceptual and empirical overlap with optimism in the context of generative AI chatbot adoption. The structural model of the study is presented in figure 1.

Figure 1. Conceptual framework



Source: Prepared by the authors

Perceived ease of use (PEU) refers to the extent to which a chatbot's interface is perceived as user-friendly, including simplicity, ease of navigation, clarity of instructions, and effective error handling. Prior studies indicate that the perceived ease of using a chatbot significantly affects users' willingness to adopt and engage with AI-based technologies. According to TAM, individuals are more likely to accept a technology when they perceive it as simple and effortless to use (Yenkatesh et al., 2003). This principle is supported by more recent research confirming the substantial role of PEU in shaping both adoption intention and actual engagement with AI-based technologies (Duenser & Douglas, 2023; Hasan et al., 2024; Saihi et al., 2024). Perceived usefulness (PU) reflects the degree to which a technology enhances the effectiveness of its users. In the context of AI chatbot adoption in education, PU includes benefits such as saving time, reducing effort, providing rapid responses, and automating repetitive tasks. Previous studies consistently show that PU and performance expectancy strongly shape user attitudes and behaviours toward AI chatbots and influence overall satisfaction (Hasan et al., 2024; Koo et al., 2025; Pizzi et al., 2021; Rana et al., 2024).

Optimism, as defined by Parasuraman (2000), refers to a positive view of technology and the belief that it enhances personal control, flexibility, and efficiency in everyday life. Individuals with higher levels of optimism are generally better able to cope with negative experiences, which in turn improves their perceived ease of use of technology (Hasan et al., 2024; Parasuraman & Colby, 2015; Meldebekova et al., 2026). Users who perceive AI technologies as beneficial are therefore more likely to accept them. On this basis, the following hypothesis is proposed:

H_1. Optimism positively influences the perceived ease of use of AI chatbots in education.

According to TAM, perceived ease of use is positively related to perceived usefulness and also positively influences users' behavioral intention (BI) to adopt technology (Yenkatesh et al., 2003). Behavioral intention refers to a user's conscious decision or plan to incorporate a new technology into everyday activities (Yadegari et al., 2022). Accordingly, the following hypotheses are proposed:

H_2. The perceived ease of use of AI chatbots in education is positively related to perceived usefulness.

H_3. The perceived ease of use of AI chatbots positively influences students' behavioral intention.

Perceived usefulness is also recognized as a strong predictor of behavioral intention and is considered fundamental in shaping users' decisions to adopt technology. TAM emphasizes that an individual's willingness to embrace a new technology depends largely on its perceived ease of use and perceived usefulness (Davis, 1989; venkatesh et al., 2003). Empirical findings suggest that individuals are more likely to adopt technology when they perceive it as effective, beneficial, and relevant to their needs (Hasan et al., 2024; koo et al., 2025; rana et al., 2024; Saihi et al., 2024). For example, Jo and Baek (2023) found that perceived usefulness significantly affects the intention to continue using intelligent personal assistants. Therefore, the following hypothesis is advanced:

H_4. The perceived usefulness of AI chatbots positively influences students' behavioral intention.

In predicting technology acceptance, especially the perceived trustworthiness of AI-based technologies, transparency and ethics play a particularly important role. Transparency/Ethics refers to the extent to which AI systems are developed and operate in ways that align with societal values and ethical norms, thereby enabling users to understand, evaluate, and trust these systems (Duenser & douglas, 2023; Hunter, 2023; Olateju et al., 2024). The balance between AI-generated insights and user values is especially important in decision-making processes, highlighting the need for AI systems to meet user expectations and ethical standards (Kumar & Bargavi, 2024). On this basis, the following hypotheses are proposed:

H_{5a}. Transparency/ethics of AI chatbots positively influences students' behavioral intention.

H_{5b}. Transparency/ethics of AI chatbots positively influences students' use behaviour.

Across a range of educational technologies, previous studies have demonstrated a positive relationship between behavioral intention and actual use behavior (Hasan et al., 2024; Rana et al., 2024). However, use behavior may change over time as a result of new information, shifting perceptions, or changes in the educational environment.

H_6. Behavioral intention positively influences use behaviour of AI chatbots by students.

3. METHODOLOGY

3. 1. RESEARCH DESIGN

This study aims to explore the factors influencing generative AI chatbots' adoption among university students by employing a quantitative research design grounded in established theoretical models, namely TR and TAM-related constructs. The research model incorporates seven latent variables, namely, Optimism (Opt), PEU, PU, Transparency/Ethics (Tr/E), Behavioral Intention to use (BI), and actual Use Behavior (BU). In line with survey-based technology adoption research, actual use behavior (BU) is operationalized as self-reported academic use of generative AI chatbots, rather than objectively recorded usage.

3. 2. INSTRUMENT DEVELOPMENT

The primary data collection instrument was a structured online questionnaire developed using google forms. It included 18 measurement items across six latent constructs, adapted from validated scales in previous studies (Hasan et al., 2024; Koo et al., 2025; Rana et al., 2024). Because objective system usage data were not available, use behaviour (BU) was measured through self-reported items reflecting actual academic use and engagement with generative AI chatbots, an approach commonly applied in prior TAM- and AI-related research (Rana et al., 2024; Hasan et al., 2024). These items assessed the extent to which students actively used AI chatbots for study-related tasks and decision support. All items were measured on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The survey also included demographic variables, namely gender, age, and field of study, as well as screening questions related to prior frequency of generative AI chatbot use. To ensure clarity and accessibility for the target population, the questionnaire was translated into Russian.

Table 1 presents the study variables, measurement items, and their corresponding sources.

Table 1. Variables and sources

Opt 1	Interactive AI/Chatbot uses the newest technologies are much more convenient to use	Optimism (opt)	(Hasan et al., 2024)
Opt2	Interactive AI/Chatbot makes me more efficient in my academics/study		
Opt3	I prefer to use the most advanced Interactive AI/Chatbot technology available.		
PEU1	Learning to use Interactive AI/Chatbot would be easy for me	Perceived easy of use (PEU)	(Hasan et al., 2024)/ (Rana et al., 2024)
PEU2	Usage of Interactive AI/chatbot is clear and understandable to me		
PU1	The use of Interactive AI/Chatbot enables me to finish my work more quickly.	Perceived usefulness (PU)	(Hasan et al., 2024)/ (Rana et al., 2024)
PU2	The use of Interactive AI/Chatbot increases my productivity		
Tr/E1	Interactive AI/Chatbots are transparent in their performance	Transparency/ Ethics (Tr/E)	(Koo et al., 2025; Rana et al., 2024)
Tr/E2	Interactive AI/Chatbots do not collect more information than they need.		
Tr/E3	Interactive AI/Chatbots protect and do not disclose my personal information to other parties.		
BI1	Whenever possible, I intend to frequently use an Interactive AI/Chatbot in my academics/study	Behavioral intention (BI)	(Rana et al., 2024)
BI2	I intend to use an Interactive AI/Chatbot when it is legally accepted for my works/institutions		
BI3	I intend to use an Interactive AI/Chatbot		
BU1	I use an interactive AI/Chatbot to assist me in my academics/study	Use behavior (BU)	(Hasan et al., 2024; Rana et al., 2024)
BU2	I utilize the Interactive AI/Chatbot to verify my decisions.		
BU3	I like working with an interactive AI/Chatbot.		

Source: Prepared by the authors

3. 3. SAMPLING AND DATA COLLECTION

The target population of this study comprised undergraduate university students in Kazakhstan who are likely to interact with generative AI chatbot technologies as part of their academic activities. The sample was drawn from students enrolled at Astana IT University, a specialized higher education institution with a focus on information technology, digital innovation, and data-driven disciplines. This population is particularly suitable for examining AI chatbot adoption, as students in these programs are more likely to possess basic digital competencies and prior exposure to AI-based tools used for learning, programming, and information retrieval.

A purposive sampling approach was employed, and data were collected from undergraduate students at Astana IT Un[2]iversity. The focus on IT students is consistent with the study's objective of examining users who are relatively technologically proficient and therefore more likely to have prior experience with AI chatbot technologies.

To ensure an adequate sample size for multivariate analysis, a priori power analysis was conducted using G*Power 3.1 software. With six predictors, a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and statistical power of 0.80, the minimum required sample size was estimated at 98. To enhance robustness and better account for model complexity, the assumed effect size was reduced to $f^2 = 0.05$, resulting in a revised minimum sample size of 279 respondents. Data were collected from April to the end of May 2025. In total, 285 valid responses were obtained, corresponding to an estimated response rate of approximately 34%.

3. 4. DATA ANALYSIS APPROACH

The data were analysed using partial least squares structural equation modelling (PLS-SEM), which is well suited for predictive modelling and theory development when dealing with latent constructs (Henseler et al., 2015). The analysis was performed using SmartPLS 4 software (Ringle et al., 2024). PLS-SEM was selected because of its suitability for evaluating complex models with small to medium sample sizes and its robustness in handling non-normal data distributions.

Before assessing the structural model, the measurement model was evaluated to ensure construct reliability, convergent validity, and discriminant validity. Standard evaluation criteria were applied, including Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and discriminant validity assessed through the Heterotrait-Monotrait (HTMT) ratio of correlation. Subsequently, additional diagnostic tests were conducted to examine multicollinearity using variance inflation factors (VIF), effect sizes (f^2), and predictive relevance (Q^2). Finally, hypothesis testing was carried out to determine whether hypotheses 1 through 6 were supported.

4. RESULTS

The final sample consisted of 285 respondents. The demographic profile was as follows: 153 female students (53.7%), 130 male students (45.6%), and 2 respondents who did not report their gender (0.7%). In terms of age, 231 respondents (81%) were aged 18-24, 31 respondents (11%) were aged 25–34, and 23 respondents (8%) were aged 35-44. With regard to the frequency of interactive AI/chatbot use, 16 respondents (6%) reported using such tools several times per month, whereas the majority, 269 respondents (94%), indicated very frequent use, defined as weekly or daily.

4. 1. RELIABILITY AND VALIDITY

As shown in table 2, all item loadings were statistically acceptable, with no loading falling below the threshold of 0.70. Indicators of convergent validity were also satisfactory, as all average variance extracted (AVE) values exceeded 0.50. Composite reliability values were above 0.80, indicating strong internal consistency of the latent constructs, while Cronbach's alpha values exceeded 0.70, further confirming construct reliability.

Table 2. Reliability and validity of measurement models

Variables	Outer Loading	AVE	CR	Cronbach's Alpha
OP1	0,928	0,615	0,823	0,819
OP2	0,788			
OP3	0,701			
PEU1	0,935	0,872	0,932	0,932
PEU2	0,933			
PU1	0,959	0,846	0,916	0,915
PU2	0,878			
Tr/E1	0,785	0,671	0,859	0,860
Tr/E2	0,748			
Tr/E3	0,916			
BI1	0,781	0,636	0,839	0,838
BI2	0,756			
BI3	0,853			
BU1	0,824	0,717	0,883	0,883
BU2	0,888			
BU3	0,827			

Source: Prepared by the authors

Henseler et al. (2015) demonstrated through simulation that the Fornell–Larcker criterion is not always sufficient for assessing discriminant validity. They therefore proposed the heterotrait-monotrait (HTMT) ratio as a more robust alternative. In the present study, table 3 shows that all HTMT values were below the recommended threshold of 0.90, confirming satisfactory discriminant validity across all constructs.

Table 3. Heterotrait-monotrait ratio (HTMT)

	opt	PEU	PU	Tr/E	BI
opt					
PEU	0,681				
PU	0,792	0,883			
Tr/E	0,804	0,616	0,725		
BI	0,825	0,808	0,848	0,760	
BU	0,695	0,588	0,665	0,749	0,849

Source: Prepared by the authors

The results further indicate that the full collinearity variance inflation factor (VIF) values for all constructs were below the recommended threshold of 5.00 (Henseler et al., 2015), as reported in table 4. This suggests that multicollinearity was not a concern in the present dataset.

Table 4. Multicollinearity test results

Variables	VIF
BI1	2,361
BI2	1,756
BI3	1,980
BU1	2,951
BU2	3,091
BU3	2,050
Opt1	2,031
Opt2	1,938
Opt3	1,648
PEU1	4,283
PEU2	4,283
PU1	3,309
PU2	3,309
Tr/E1	1,939
Tr/E2	2,249
Tr/E3	2,404

Source: Prepared by the authors

Table 5 presents the f^2 effect size values for the latent constructs. In line with the recommendations of Henseler et al. (2015; 2016), effect size assessment extends beyond statistical significance to evaluate the substantive strength of the relationships. According to these guidelines, f^2 values above 0.35 indicate strong effects, values above 0.15 indicate moderate effects, and values above 0.02 indicate weak effects. The findings in table 5 show a strong effect of perceived ease of use (PEU) on perceived usefulness (PU), as well as a strong effect of behavioral intention (BI) on use behavior (BU), whereas the remaining relationships exhibit weak effects.

Table 5. Effect size (f2) results

Variables	Original sample (O)	Description
BI -> BU	0,692	High effect
Opt -> PEU	0,879	High effect
PEU -> BI	0,099	Small effect
PEU -> PU	0,511	High effect
PU -> BI	0,088	Small effect
Tr/E -> BI	0,221	Medium Effect
Tr/E -> BU	0,105	Small effect

Source: Prepared by the authors

Predictive relevance was assessed using the Q^2 statistic, which evaluates the model's ability to predict the endogenous constructs (Hair et al., 2013). In PLS-SEM, Q^2 values greater than 0 indicate predictive relevance, with values of 0.02, 0.15, and 0.35 reflecting small, medium, and large predictive relevance, respectively. As presented in table 6, the results indicate that the model demonstrates substantial predictive relevance for the endogenous variables.

Table 6. Predictive relevance test results (Q^2)

Variables	Q^2predict
PEU	0,366
PU	0,436
BI	0,501
BU	0,455

Source: Prepared by the authors

4. 2. STRUCTURAL MODEL TESTING

The results of the structural model and hypothesis testing are presented in table 7 and illustrated in figure 2. The adjusted R^2 values shown in figure 2 indicate the explanatory power of the predictor variables for each endogenous construct. The findings reveal that optimism explains 46.8% of the variance in PEU ($R^2 = 0.468$), while PEU explains 77.8% of the variance in PU ($R^2 = 0.778$). In turn, PEU, PU, and Transparency/Ethics explain 78.3% of the variance in BI ($R^2 = 0.783$), whereas BI and transparency/ethics explain 74.2% of the variance in actual use behaviour (BU) ($R^2 = 0.742$).

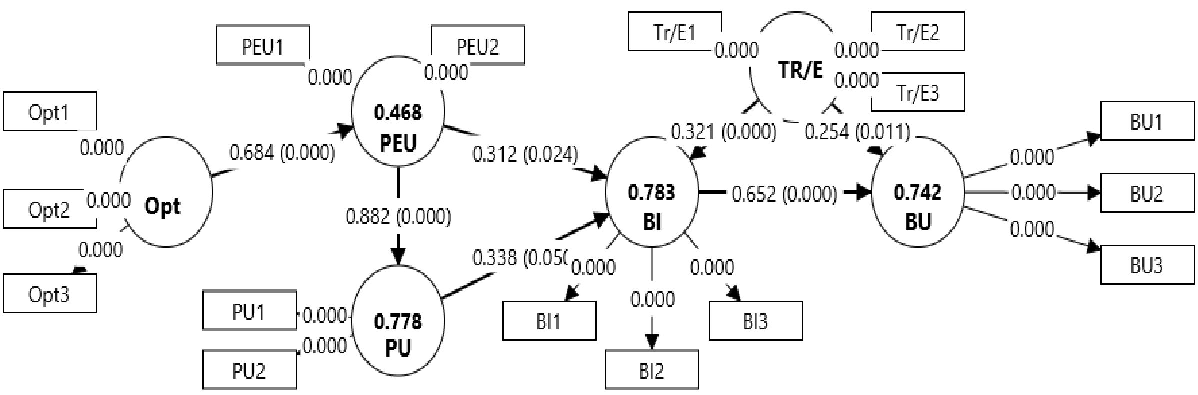
Table 7. Evaluation of the structural model

Hypothesis	Variables	Beta	T statistics	p values	Decision
H_1	Opt -> PEU	0,684	12,671	0,000	Supported
H_2	PEU -> PU	0,882	31,370	0,000	Supported
H_3	PEU -> BI	0,312	2,257	0,024	Supported
H_4	PU -> BI	0,338	1,964	0,050	Supported
H_{5a}	Tr/E -> BI	0,321	3,585	0,000	Supported
H_{5b}	Tr/E -> BU	0,254	2,559	0,011	Supported
H_6	BI -> BU	0,652	6,373	0,000	Supported

Source: Prepared by the authors

Following the recommendation of Hair et al. (2013), a bootstrapping procedure with 5,000 subsamples was used to test the statistical significance of the relationships between exogenous and endogenous constructs. Figure 2 presents the PLS-SEM results, including path coefficients and p-values.

Figure 2. Structural model results



Source: Prepared by the authors

The results reported in table 7 provide strong support for the proposed hypotheses. Since all t-values exceeded 1.96 and all p-values were below the accepted significance threshold, all hypotheses were supported. The relationship between optimism and PEU was positive and significant, supporting H_1 (β = 0.684, p = 0.000). The effect of PEU on PU was also strong and significant, supporting H_2 (β = 0.882, p = 0.000). The positive direct effect of PEU on BI supported H_3 (β = 0.312, p = 0.024). In addition, PU positively influenced students' behavioral intention to use interactive AI/chatbots, thereby supporting H_4 (β = 0.338, p = 0.050). Transparency/ethics positively influenced both BI and BU, supporting H_{5a} (β = 0.321, p = 0.000) and H_{5b} (β = 0.254, p = 0.011), respectively. Finally, BI exerted a positive and significant effect on BU, providing support for H_6 (β = 0.652, p = 0.000).

5. DISCUSSION

The present study examined the key behavioral and perceptual factors shaping the adoption of generative AI chatbots among technologically proficient university students in Kazakhstan. The findings largely support the applicability of established technology adoption theories to generative AI in higher education.

Consistent with prior research based on the technology readiness index (Hasan et al., 2024; Parasuraman & Colby, 2015), optimism significantly influenced perceived ease of use. The strong path coefficient (β = 0.684, p = 0.000) indicates that students who view technology as beneficial and efficiency-enhancing are more likely to perceive AI chatbots as accessible and intuitive. This result aligns with Hasan et al. (2024), who reported similar patterns among students in the United States and Asia.

In line with the technology acceptance model (Davis, 1989), both perceived ease of use and perceived usefulness were significant predictors of behavioral intention. The positive effect of perceived ease of use on perceived usefulness confirms that systems regarded as simple and clear to use are also more likely to be viewed as valuable in academic settings. This supports earlier TAM-based findings and suggests that usability remains a central determinant of adoption, even as AI technologies become increasingly sophisticated. In addition, both perceived ease of use (β = 0.312) and perceived usefulness (β = 0.338) significantly predicted behavioral intention, indicating that students are more likely to adopt AI chatbots when they perceive them as both user-friendly and beneficial for academic performance.

A key contribution of this study is the inclusion of transparency and ethics (Tr/E) in the adoption framework, a dimension increasingly recognized yet still underexamined in empirical research (Dignum, 2018; Olateju et al., 2024). Unlike conventional trust constructs, which generally reflect confidence in a technology or provider, Tr/E refers more specifically to perceived openness, fairness, responsible data use and ethical system behavior. In the context of generative AI chatbots, this includes understanding how responses are generated, how data are handled, and whether the system operates in a fair and socially responsible manner.

The results show that Tr/E positively affects both behavioral intention (β = 0.321) and actual use behavior (β = 0.254). This suggests that students consider fairness, transparency, and responsible data practices to be important criteria in adopting AI tools. This finding is consistent with recent research emphasizing the growing importance of trust and algorithmic transparency in the adoption of large language model-based systems (Duenser & Douglas, 2023). Thus, students' willingness to use AI chatbots appears to depend not only on performance-related benefits but also on the perceived ethical legitimacy of such systems.

The positive relationship between behavioral intention and actual use behavior further supports the technology acceptance model and its extensions (Venkatesh et al., 2003), reaffirming intention as a reliable predictor of actual technology use.

Compared with similar studies conducted in North America and the Gulf region (Hasan et al., 2024; Saihi et al., 2024), this study offers a region-specific perspective from Central Asia.

While the relevance of perceived ease of use and perceived usefulness appears robust across contexts, the inclusion of transparency and ethics adds an important socio-cultural dimension. Students in Kazakhstan appear to be attentive not only to technical functionality but also to the ethical legitimacy and broader social implications of AI technologies.

These findings have important implications for higher education policy and practice. Universities should prioritize user-friendly AI tools and provide clear guidance on their appropriate academic use. Institutions may also need to establish frameworks addressing academic integrity, responsible AI use, and data transparency. The significance of transparency and ethics further indicates that students evaluate AI systems not solely in terms of functionality, but also in relation to fairness, accountability, and responsible data governance. Integrating AI literacy into university curricula may therefore encourage more informed and ethical engagement with generative AI.

More broadly, this study contributes to understanding AI adoption in education beyond purely technical determinants. Because the research was conducted at a technology-oriented university in Kazakhstan, contextual and cultural factors may have shaped the observed adoption patterns. Technology readiness, institutional norms, and regulatory environments may all influence how students perceive and use AI tools. Future cross-cultural and multi-institutional research is needed to assess whether these determinants operate similarly across disciplines and national settings, thereby improving the generalizability of AI adoption models in higher education.

6. CONCLUSION

This study examined the determinants of generative AI chatbot adoption among university students through an integrated framework combining the technology acceptance model, the technology readiness index, and transparency/ethics. The findings show that perceived ease of use and perceived usefulness remain significant predictors of behavioral intention, confirming the continued relevance of established technology adoption theories in the context of emerging AI tools. Behavioral intention also significantly predicted actual use behavior, in line with prior technology acceptance research.

The results further underscore the importance of psychological readiness and ethical considerations in shaping students' attitudes toward AI chatbot technologies. In particular, transparency and ethical use were found to positively influence adoption decisions, suggesting that responsible AI design is becoming increasingly important for the acceptance of generative AI tools in educational settings.

Despite these contributions, the study has several limitations. First, the cross-sectional design captures perceptions and behaviors at a single point in time; therefore, causal relationships among the constructs should be interpreted cautiously. Future research should employ longitudinal designs to examine how students' perceptions and usage patterns evolve as generative AI technologies become more deeply integrated into education.

Second, the study relies on self-reported survey data, which may be subject to biases such as social desirability and reporting inaccuracies. Although such measures are common in technology adoption research, future studies could enhance measurement validity by incorporating objective usage data drawn from learning platforms or AI systems.

Third, the study used purposive sampling from a single institution, Astana IT University, which primarily focuses on information technology and digital disciplines. Students in such fields may exhibit higher levels of technological familiarity and readiness than students from non-technical disciplines.

Finally, the findings may have limited generalizability beyond the specific educational and national context examined. Cultural, institutional, and technological factors influencing AI adoption may vary across countries and academic disciplines. Future research should therefore include multiple universities, students from more diverse academic backgrounds, and cross-national comparisons to strengthen the external validity of the findings.

Overall, this study provides a timely and evidence-based framework for understanding how students perceive, accept, and use AI chatbots in educational contexts. As generative AI continues to reshape higher education, a student-centered and ethically responsible approach to technology adoption will be essential for realizing its transformative potential.

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