Discover Education

RESEARCH Open Access

Factors affecting ChatGPT adoption among Bangladeshi university students with the moderating role of social influence

Kamron Naher[1], Kazi Omar Siddiqi[2], Mohammad Abdullah Al Mamun[3], Sagata Chakma[4,5], Farzana Rashid[6], Umme Hany Arju[7], Sahin Alam[8] and Tipon Tanchangya[9*]

*Correspondence:
Tipon Tanchangya
tipon.tcg.edu@gmail.com

Full list of author information is available at the end of the article

Abstract

The integration of artificial intelligence (AI) into classrooms has revolutionized academic learning, presenting both opportunities and obstacles for learners' advancement. The study aims to explore the factors of Extended technology acceptance model (TAM) by adding external variables such as information quality (IFQ), interaction quality (ITQ), and system quality (SQ) from DeLone & McLean's theory. The data were collected from university students, and the analysis was conducted using partial least squares structural equation modeling (PLS-SEM). The result of the study shows that IFQ and ITQ have a positive influence on perceived usefulness (PU) and perceived ease of use (PEU), respectively. Additionally, PU and PEU are positively related. Moreover, the moderating role of social influence (SI) is true in this study. Theoretically, the study integrates the extended TAM model. Our study was able to contribute to our existing knowledge of the primary antecedents of the TAM model by integrating DeLone & McLean's theory to understand the attitude (ATT) of students toward ChatGPT in the case of Bangladesh. The research can be an insightful direction for academicians, marketers, and educators who want to capitalize on ChatGPT and promote the usage of AI among students for their productive learning.

Keywords Information quality, Interaction quality, Social influence, ChatGPT adoption, Technology Acceptance Model (TAM), University students

1 Introduction

The inclusion of AI in education has completely transformed learning in academia, providing possibilities as well as challenges for the growth of learners. The application of AI in higher education has risen significantly over the past eight years, along with an extensive development of new AI technologies [1]. As the popularity of AI-based tools rises, students recognize the multitude of factors that influence their consciousness, credibility, and usage of ChatGPT in the context of learning [2]. AI tools, including ChatGPT, have drastically changed the conventional education methods by offering innovative

© The Author(s) 2026. **Open Access** This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by-nc-nd/4.0/.

instruction and learning facilities. It also assists teachers to develop quizzes, projects, assignments, presentations, and other interactive materials that modify learning instruction, which are matched with students' needs and preferences [3]. Furthermore, students must understand the accessibility and what benefits ChatGPT provides, which is essential for improving broader connectivity and educational possibilities [4]. ChatGPT is not without limitations and biases, so it is essential to consider the terms and conditions of adoption. These acknowledgements stimulate students` levels of confidence towards technological concerns and build up a positive mindset so that they can use it in their learning processes.

It is evident that ChatGPT brings numerous benefits for cognitive education, but it is more important to understand what factors impact its adoption; it is more essential for a satisfactory implementation [5]. Over the years, several empirical studies have been carried out in different technological domains with various conceptual frameworks and approaches, but there is a paucity of research on the contexts of factors affecting the adoption of AI-powered chatbots, such as ChatGPT, in educational contexts [6]. Among the existing studies, the Technology Acceptance Model (TAM) was introduced as an initial model to explain the technological model [7]. The Theory of Reasoned Action explained that the focus of TAM theory is examining the attitude of end-users towards embracing new technology, centred on perceived ease of use and perceived usefulness [8]. Moreover, the latest studies argue that more comprehensive understandings are required to examine other variables such as perceived enjoyment, trust, self-efficacy, personal innovativeness, and satisfaction [9]. In addition, the role of social influence is a key mechanism that influences students to use AI tools, and the variable has become increasingly important as a moderating component of embracing technology [10]. Numerous research studies have been conducted in various countries on these dynamics, but there is no existing research in the context of Bangladeshi higher education. Furthermore, there are a few studies that found integrating both adoption and user satisfaction in a single model, particularly in the scope of Bangladeshi higher education. As Bangladesh concentrates more on transforming conventional education methods into digital methods, it is becoming crucial to measure how AI tools such as ChatGPT affect users and their impact on student satisfaction [9].

This study aims to find out this gap by investigating the core parameters modifying ChatGPT user adoption and overall user experience among university learners in Bangladesh. The crucial aim of this study is to examine the moderating effects of social influence. In Bangladeshi contexts, numerous studies have been conducted on the variables that contribute to the adoption and usage of ChatGPT; there is a paucity of research concentrating on the contribution of information, interaction quality, and system quality on perceived utility, perceived ease of use, and the intention to use ChatGPT among Bangladeshi students of higher education institutions. This study uses different variables from the TAM and DeLone & McLean theories. This study provides insights into the factors shaping ChatGPT adoption in higher education by incorporating information quality, interaction quality, and system quality into extended technology adoption frameworks. Furthermore, this study provides valuable information about information distribution, ensuring that students receive reliable, valuable, relevant, and authentic knowledge regarding ChatGPT.

Our research significantly focuses on the contribution of social influence to the wide adoption of ChatGPT through providing real-time information and identifying trends in other contexts, as revealed by studies. The correlation between students' willingness to adopt technology and their mindset of ChatGPT as a significant resource for knowledge application underscores broader dimensions of technological acceptance theories, especially those centred on perceived utility. By investigating these dynamics, this study addresses a critical research gap: contemporary literature often treats technology acceptance as an isolated, system-driven cognitive calculus, largely ignoring how system-level success metrics interact with external socio-cultural factors in developing, collective learning environments. While it may appear that our framework simply synthesizes pre-existing models—specifically the Technology Acceptance Model (TAM), the DeLone & McLean IS Success Model, and the Unified Theory of Acceptance and Use of Technology (UTAUT)—this integration is conceptually necessary to redefine traditional boundaries. Theoretically, beyond personal views, social influence functions as a collective factor in academic environments. Students rely on feedback from peers, faculty, and online communities to assess emerging technology, which speeds up adoption and minimizes uncertainty. This points to a distinct theoretical advancement: in a highly collectivistic environment, systemic quality metrics (Information, Interaction, and System Quality) do not automatically drive adoption; they are heavily filtered and moderated through Social Influence (SI) as defined by UTAUT. Thus, the geographic setting functions as a conceptual vehicle to map how collective student cultures alter baseline technology acceptance pathways. In Bangladesh's developing higher-learning context, social impact is crucial to bridge the gap between technological capability and real-life classroom incorporation. This study proves that adoption is a socially constructed process where peer-driven momentum plays a critical role in long-term engagement. Practically, these findings provide a blueprint for university administrators to formulate pedagogical policies that leverage peer dynamics, while helping developers optimize conversational AI interfaces for collaborative learning cultures.

2 Theoretical background and hypotheses development

2.1 Theoretical background

The present study is grounded in an extended Technology Acceptance Model (TAM), augmented by constructs from the DeLone & McLean IS Success Model and the Unified Theory of Acceptance and Use of Technology (UTAUT). In its original formulation, TAM posits that PU and PEU are the primary antecedents of a user's ATT toward a system, which in turn predicts Behavioral Intention (BI) and ultimately actual use [11]. DeLone and McLean [12] proposed a metric to assess the effectiveness of information systems. Çelik & Ayaz [13] comprises system quality, information quality, service quality, system usage or intention to use, user happiness, and the system's overall advantages. Gürkut & Nat [14] sought to determine how academic and administrative staff members' satisfaction with the Student Information System was affected by System Quality, Information Quality, and Information Presentation. The study's findings indicate that user happiness is directly impacted by system quality and information quality elements. So, in this paper, in addition to two important variables, the researchers have blended IFQ, ITQ, and SQ. IFQ and SQ are adopted from the study proposed by DeLone [15] to understand students' attitudes regarding the adoption of ChatGPT. Thus, our proposed

model adds new insight to the existing body of literature by blending two theories in one frame. It explores the psychological perception (PU, PEU, and ATT), drivers of quality of ChatGPT (FQ, ITQ, and SQ), and the social determinants (PE, EE, and SI).

While this baseline integration of DeLone & McLean's quality constructs (IFQ, ITQ, SQ) into the TAM framework builds upon foundational attempts in contemporary literature, such as Almulla (2024) [16], our study introduces distinct theoretical advancements that go significantly beyond existing boundaries. Rather than merely replicating established direct paths, this research clarifies the unique theoretical value of AI adoption through three specific contributions. First, we introduce the moderating mechanism of SI within this integrated matrix, modeling technology adoption as a socially constructed phenomenon rather than an isolated cognitive process. Second, this research shifts the analytical lens to a developing South Asian educational ecosystem (Bangladesh), proving that in collective learning cultures, systemic quality variables are heavily filtered through social structures before transforming into actual use. Finally, this study refines the conceptual boundaries of ITQ specifically for Generative AI, demonstrating that conversational, prompt-dependent AI interactions expand the traditional limits of TAM in higher education. Kibria et al. [17] reported that social influence significantly affects university students' adoption of ChatGPT in Bangladesh, highlighting the importance of peer networks and social environments in shaping AI adoption behaviour. While system quality and perceived usefulness drive technology acceptance, the literature also emphasizes the negative dimensions of AI adoption. University students often experience a sense of perceived risk and privacy concerns regarding how their data is handled by generative AI tools [18, 19]. Additionally, issues related to academic integrity and plagiarism function as critical counter-weights that can hinder long-term student trust and adoption.

2.2 Hypothesis development

2.2.1 The influence of information quality on PU

Information quality refers to the calibre of output generated from the information system in use [20]. Good information increases user confidence and favourably affects perceived usefulness. Perceived usefulness is defined as the degree to which a person believes that utilising a certain set of systems may significantly increase their performance [11, 21]. Information quality has gained significant importance for measuring the performance of e-learning systems. Mun & Hwang [1] showed that information usefulness and source trust were substantially correlated with the information provided by ChatGPT in terms of its correctness, richness, timeliness, format, and relevancy. Through perceived ease and perceived usefulness, Mahmud et al. [9] confirmed that the quality of information, systems, and services significantly affects perceived usefulness in the impact of big data quality features on user satisfaction. Holsapple & Lee-Post [22, 23] found that IQ is a fundamental component of system design. To gauge information quality from the perspective of the students, they used course content attributes like how well-structured, effectively presented, appropriate in length, understandable, and current the material was. Based on the above discussion, the following hypothesis has been developed.

H1 Information Quality positively influences Perceived Usefulness.

2.2.2 The influence of information quality on PEU

Perceived ease of use (PEU) is the degree to which a person believes that a technology or information system will be comparatively straightforward and simple to use [11]. Legramante et al. [24] verified that perceived ease of use is positively impacted by information quality. PEU has a beneficial effect on PU, which in turn has a good effect on behavioural intention and user happiness. As characteristics of an informative mobile app, system, and information quality were found to have little influence on PU. The fact that usefulness during the pre-adoption stage is crucial in forming beliefs may be the reason for the two elements' insignificance on PEU [25]. The information quality had a profound effect on people's continual involvement with the integrated e-learning programme [26]. It is evident that a standard website and content positively influence users' level of happiness, which has a significant correlation with end users' attitude and intention. The comparison of the two groups revealed substantial variations in the influence of information quality on satisfaction with information and perceived usefulness on usage intention [27, 28]. Therefore, the study proposes the research hypothesis:

H2 Information Quality positively influences Perceived Ease of Use.

2.2.3 The influence of interaction quality on PEU

ITQ refers to the perceived responsiveness, coherence, and conversational richness of a system's interface and outputs [24]. High ITQ in conventional AI tools, including ChatGPT, ensures that users feel conversations are natural, engaging, and context-aware, and users have a favourable attitude that such tools are useful and effortless. Previous studies indicated that there is a distinct "Effectiveness" construct connected with ITQ and that it has a significant relationship with PU and an inverse relationship with reported anxiety, indicating smoother, more effortless interactions [10]. Both educators and learners experienced that a high level of intelligent and coherent interaction with ChatGPT influenced users' attitudes towards the system's utility and ease. Therefore, we formulated the following hypothesis:

H3 Interaction Quality positively influences Perceived Usefulness.

2.2.4 The influence of interaction quality on PE

ChatGPT is a cutting-edge technology that acts as an intelligent system for making more productive lectures, creating presentations, and academic writing [29] and programming skills [30]. It can make users more analytical in learning to support them through offering personalized learning [31]. As an effective communicative agent, it gives the learners a significant chance to grow their reasoning abilities as a challenging outcome of learning with low-stakes practices [32]. An empirical investigation has been made on ChatGPT acceptance among higher education users by extending the TAM model to incorporate "Perceived Intelligence" (like ITQ) as a predictive factor [3]. Findings indicated that both perceived intelligence and PE significantly influence adoption intentions; additionally, perceived intelligence demonstrated a robust positive impact on PU and indirectly facilitated PE by reducing interaction friction [33]. Accordingly, we have hypothesized:

H4 Interaction Quality positively influences Perceived Ease of Use.

2.2.5 System quality impact on PE

System quality refers to the distinctive features of an information system, including reaction speed, convenience, dependability, adaptability, usefulness, simplicity of use, and learning [34]. SQ has been identified as a critical factor in determining the system's performance and directly affects how beneficial students believe the system to be [35, 36]. SQ and IFQ were found to be the primary drivers of users' intentions and contentment about e-learning usage, and demonstrated that user intentions and satisfaction predict real e-learning use [37]. It was found by Gupta et al. [25] that PU was unaffected by the system and information quality of an informative mobile app. Because usefulness at the pre-adoption stage is crucial for forming beliefs, the limited impact of these two elements on PU may be explained. Alkhawaja et al. [38] demonstrated that perceived usefulness and intention to use are strongly influenced by system quality, how intention to use and actual usage are greatly influenced by perceived usefulness, and how actual use of the e-learning system is significantly influenced by intention to use. Recent evidence from ChatGPT adoption studies suggests that reliable system performance, responsiveness, and functional effectiveness significantly enhance students' perceptions of usefulness and trust toward AI technologies [39]. In the case of Bangladeshi students' attitude towards using ChatGPT, no studies have shown the association between system quality and perceived usefulness. So, the following hypothesis has been developed:

H5 System Quality positively influences Perceived Usefulness.

2.2.6 System quality influence on PEU

The quality of an Internet-based system is primarily determined by its ease of use and perceived utility. Scholars discovered that website features have a significant impact on user acceptability, highlighting the importance of consumer acceptance in any applied system [35]. According to Ghazal et al. [40], e-learning systems with technical problems and other challenges may have a detrimental effect on users' intentions to use them, and system quality has a bigger impact on users' desire to use. According to Fitria et al. [41], the perceived ease of use of e-learning systems correlates positively with system quality. Dokhanian et al. [42] showed that system quality has a favourable and considerable impact on perceived ease of use and usefulness. In the case of Bangladeshi students' attitude towards using ChatGPT, no studies have shown the association between system quality and perceived ease of use. In the context of generative AI, Dorobăț and Corbea [39] reported that well-functioning AI systems with consistent performance and user-friendly interfaces contribute significantly to users' perceptions of ease of use. So, the following hypothesis has been developed:

H6 System Quality positively influences Perceived Ease of Use.

2.2.7 Impact of perceived usefulness (PU) on perceived ease of use (PEU)

Among the components of TAM, perceived utility and PEU are the primary drivers that directly or indirectly explain the decision to embrace new technologies [43]. Brzustowicz [44], in their study on adopter analysis in the case of artificial intelligence, found

that users develop a positive mindset to use technology when they find it user-friendly and comfortable. Biswas [45] also investigated that user-friendly AI increases users' productivity and people find it useful. AI algorithms help marketers to sort out target and loyal customers without much effort, which ultimately leads to usefulness [46]. Hasni et al. [47] corroborated the links between the initial TAM dimensions, demonstrating substantial correlations between PU and PEU with intentions for behaviour, as well as between PEU and PU. Operators of online social networking sites in the tourist business should focus on how to add value to the social network and online customers to boost their PU. Therefore, to explore how students perceive ChatGPT as easier in terms of its usefulness, we proposed the following hypothesis:

H7 Higher Perceived Usefulness (PU) positively affects Perceived Ease of Use (PEU).

2.2.8 The influence of perceived usefulness

An attitude refers to a person's favourable or negative response to an object, person, institution, event, or other distinguishing component of their environment [7]. As previously stated by the TAM, individuals' intentions to utilise a system are impacted by two fundamental beliefs: PU and PEU. These intentions influence attitudes towards utilising technology, leading to its acceptance [48]. According to TAM, PU, and simplicity of use influence people's intentions to use information systems, which can lead to actual usage [38]. Empirical research has revealed that PU is an essential factor that helps shape positive attitudes regarding the field of technology [49]. In research on college students' usage of AI-based systems, Li [50] found that perceived utility (PU) and perceived ease of use (PEU) had a favourable influence on ATT. The survey that was conducted of university students indicated that elevated PU, assessed by the degree to which ChatGPT outputs enhance learning outcomes, substantially elevated attitude toward technology (ATT) towards the instrument [51]. The extended TAM model, by introducing trust and perceived risk, confirmed that PU directly enhances ATT [3]. Dahri et al. [52] also suggested that AI-enabled learning environments improve students' engagement and academic achievement, thereby strengthening positive perceptions and attitudes toward AI-based educational technologies. Recent studies on ChatGPT adoption in higher education indicate that perceived academic benefits and performance gains are among the strongest predictors of positive attitudes toward AI technologies [53]. Based on the above discussion, the following hypothesis has been developed:

H8 Perceived Usefulness positively influences Attitude toward ChatGPT.

2.2.9 The influence of perceived ease of use

The TAM adapts products to specific technologies and has been used to assess the acceptability of AI technology. According to research, both ease of use and perceived utility influence attitudes toward AI use [51–55]. Greater PE capturing ease of formulating prompts and interpreting responses yielded a significant positive effect on ATT [9]. Also, PE exerts both a direct positive effect on ATT and an indirect effect through increased Trust in the system, as illustrated by the extended TAM model [3]. Nuryakin [56] discovered that PU positively impacts attitude towards online learning, while PEOU affects attitude but not student satisfaction. These results underscore that ease

of interaction not only shapes attitudes outright but also foster the credibility that further reinforces positive attitudes [5]. Similarly, Dahri et al. [52] found that user-friendly and interactive AI-supported learning environments enhance students' engagement and learning experiences, which subsequently contribute to more favorable attitudes toward AI technologies. Evidence from recent higher education studies suggests that when students perceive ChatGPT as easy to interact with and integrate into their learning activities, they are more likely to develop favorable attitudes toward its use [57]. Thus, the study proposed the following hypothesis:

H9 Perceived Ease of Use positively influences Attitude toward ChatGPT.

2.2.10 The influence of attitude

According to TAM, people's perception of using a system depends on two fundamental factors, such as PU and PEU. This mindset ultimately stimulates people to accept new technology [35]. Prior studies revealed that perceived risk, conducive environment, and rigorous effort motivate people to adopt AI in higher education. These factors also act as an influential element to use AI [58]. Wu et al. [33] found that previous sentiment about usefulness and ease of use greatly shaped ATT that ultimately motivates students to adopt ChatGPT for academic purposes [33]. Moreover, university teachers have a favourable mindset to use AI in their teaching practices, which leads to a favourable ATT to adopt technology like ChatGPT [10]. In different education sectors, a favourable mindset toward ChatGPT provides a significant prediction about actual adoption behaviour. Therefore:

H10: Attitude positively influences ChatGPT adoption.

2.2.11 The moderating effect of social influence

Social influence (SI) refers to the degree to which a person believes that his or her surroundings, including peers, colleagues, friends, and leaders, should use a technology. In the UTAUT model, SI acts as a direct predictor of behaviour and as a key moderator of relationships [59]. SI has made a great contribution to spreading social awareness. The positive feedback from early users stimulates people to adopt ChatGPT, and it also offers a conducive environment for its adoption [60]. University teachers experience that high SI significantly influences people to accept ChatGPT. A conducive atmosphere from leadership stimulates the pack AI adoption [10]. In addition, this study indicates that SI impacts both initial intention and higher attitudes towards ChatGPT adoption. Parveen et al. [57] found that social influence, including peer encouragement and supportive institutional environments, significantly shapes students' behavioural intention and actual use of ChatGPT in higher education. Accordingly, we hypothesize:

H11: Social Influence positively moderates the relationship between Attitude and ChatGPT adoption.

3 Methodology

3.1 Research design and method

This study adopts a quantitative research framework, which is appropriate for analyzing numerical data and examining correlations among variables using statistical techniques

(refer to Fig. 1). Data were collected from participants with prior experience using ChatGPT. A purposive sampling method was employed to ensure relevance and appropriateness of the data, as participants were selected based on specific inclusion criteria [61]. Because respondents contributed voluntarily, this approach enhanced the relevance of the dataset [62]. Although purposive sampling is a non-probability method, it is widely recognized for its ability to generate useful and contextually relevant insights when participants meet the defined criteria [63]. The focus on university students with substantial experience using ChatGPT strengthens the validity of the findings, as these participants are directly aligned with the study's objectives. This methodological approach therefore matches the study's goal of producing accurate, focused, and actionable evidence on students' experiences with ChatGPT.

3.2 Population, sampling, and sample size

The target population of this study consisted of undergraduate and postgraduate university students in Bangladesh enrolled in public, private, and national universities who had prior experience using ChatGPT for academic or personal purposes. This focus ensured that respondents possessed relevant knowledge and practical exposure to ChatGPT, enabling them to provide informed evaluations of the factors influencing its adoption and use. By concentrating on students with prior experience, the study captured insights into technology acceptance and usage behaviour among individuals most likely to integrate AI tools into their learning activities [63].

A purposive sampling technique was employed to recruit participants who met the predefined inclusion criterion of having previously used ChatGPT. Purposive sampling was considered appropriate because the study sought responses from a specific group of users rather than the general student population. Participation was voluntary, and respondents were informed about the academic purpose of the study before completing the survey.

Data were collected between January 2025 and April 2025 using a structured online questionnaire developed through Google Forms. The questionnaire link was distributed through university student networks and online communication channels commonly used by Bangladeshi students, including Facebook groups, Messenger groups, WhatsApp groups, and email networks. To further increase accessibility and participation, QR codes linked to the questionnaire were also shared through academic networks and student communities. Before proceeding with the survey, respondents were screened to confirm that they had prior experience using ChatGPT. Participation was anonymous, and no financial or material incentives were offered.

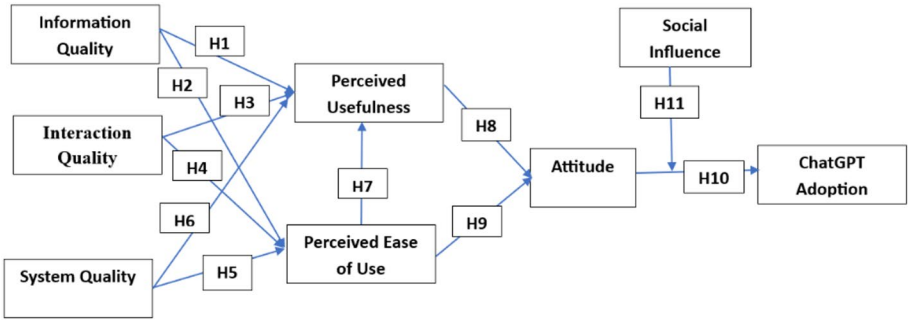

Fig. 1 Proposed research model

A total of 657 responses were initially received during the data collection period. Following a comprehensive screening process, 17 responses were excluded because of incompleteness, inconsistency, or invalid information, resulting in a final sample of 640 valid responses. To justify the adequacy of the sample size, we relied on the recommendations of Cochran (1977), which suggest that a minimum sample size of 384 is sufficient for a large population at a 95% confidence level. The final sample of 640 respondents substantially exceeded this threshold. Furthermore, the sample size was well above the minimum requirements recommended for Partial Least Squares Structural Equation Modeling (PLS-SEM), thereby enhancing the statistical power, reliability, and robustness of the findings [64].

To ensure analytical rigor and transparency, the study adopted a two-stage PLS-SEM procedure. First, the measurement model was evaluated through assessments of reliability and validity, including factor loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and heterotrait–monotrait ratio (HTMT). Second, the structural model was assessed using path coefficients, bootstrapping procedures, significance testing, and coefficient of determination (R^2) values to examine the proposed relationships among the constructs. This systematic approach provided a strong methodological foundation and enhanced the credibility of the study's findings.

3.3 Measures

In this study, the existing resources were utilised in stating the survey tools. All the items of the IFQ, ITQ, SQ, PU, PEU, SI, ATT, and CGPTA variables were evaluated using a Likert-type scale that primarily varies between strongly disagree (1) and strongly agree (5). In examining the exogenous variables IFQ and ITQ, a 4-item scale was used, and for PU, a 5-item scale was employed, as indicated by Almulla et al. [16]. For the variables like SI and ATT, 4 items were used for each factor from Al Mamun et al. [65]. Tanchangya et al. [66] validated the source of 5 items for PEU. SQ's source was Tanchangya et al. [67] and collected data by using 4 items. Finally, four items of CGPTA were collected from Alshammari & Alshammari [68].

3.4 Data analysis strategy

This study primarily utilized SPSS statistical software to analyze the data, collect respondents' demographic details, and generate descriptive statistics. Additionally, the formulated hypotheses were examined using the PLS-SEM approach. According to Dash and Paul [69], PLS-SEM serves both predictive and explanatory functions and is suitable for inductive and formative models. To uphold thorough logical reasoning, Necessary Condition Analysis (NCA), developed by Dul (2016), was also employed.

3.5 Methodological inconsistency/common method bias

The authors investigate common method bias before data analysis. The full collinearity approach and the variance inflation factor (VIF) [70], using SmartPLS [71], were utilised in this study. This investigation revealed VIF values below the established threshold of 3.3 [71] (refer to Table 1), which reflected the absence of bias in the research data.

Table 1 Common method variance/bias

Construct	ATT	CGPTA	IFQ	ITQ	PEU	PU	SI	SQ
Attitude (ATT)		2.13						
ChatGPT adoption (CGPTA)								
Information quality (IFQ)					2.39	2.70		
Interaction quality (ITQ)					2.43	2.58		
Perceived ease of use (PEU)	2.71					2.57		
Perceived usefulness (PU)	2.71							
Social influence (SI)		1.85						
System quality (SQ)					2.55	2.71		

Table 2 Demographic profile of the respondents

	Frequency	Percent
Gender		
Male	356	55.63
Female	284	44.38
Total	640	100.00
Age		
18–20 Years old	17	2.66
21–25 years old	302	47.19
26–30 years old	213	33.28
Above 30	108	16.88
Total	640	100.00
Education Level		
Bachelor	309	48.28
Masters	256	40.00
PhD	18	2.81
Others	57	8.91
Total	640	100.00
Type of University		
Public	290	50.94
Private	223	34.84
National	127	19.84
Total	640	100.00
Specialization		
Business	160	25.00
Engineering	150	23.44
Information Technology	142	22.19
Applied Sciences	122	19.06
Social Science and Humanities	66	10.31
Total	640	100.00

3.6 Profile of the respondents

The paper analysed data of 640 participants, where the majority are male ($n = 356$, 55.63%) compared to female ($n = 103$, 26.08%) (refer to Table 2). A majority of participants are in the young age range between 21 and 30 years ($n = 302$, 47.19%), and a minority are 18–20 years ($n = 17$, 2.66%). In terms of education, most of the participants held a bachelor's degree ($n = 309$, 48.28%). Most of the students were from public universities ($n = 290$, 50.94%). In the end, most of the participants were from business specialization ($n = 160$, 25%).

3.7 Descriptive statistics

Ho R. [72] suggested the following explanation for mean scores: 1-2.33 = low, 2.34–3.66 = moderate, and 3.67-5 = high (refer to Table 3). In our paper, a descriptive study, in accordance with Ho's recommendations, indicated that all constructs exhibit high means.

3.8 Assessing measurement model

A version of SmartPLS 4 (4.1.0.2) was exploited in this research for all the hypothesis testing. Although the nexus between the measurement and the structural model is assessed by PLS-SEM, particularly using ordinary least squares regression [71], Cronbach's alpha and composite reliability were exploited to assess internal consistency. Moreover, outer loadings and average variance extracted (AVE) were employed to check convergent validity. As reported by Kock [71], when Cronbach's Alpha value is 0.70, it is acceptable, although having a cutoff value of 0.8 or 0.9 is preferable. In Table 4, the suggested threshold is exceeded, as indicated by Cronbach's Alpha scores for each construct, indicating strong internal consistency. As proposed by Kock [71], the acceptable value for composite reliability must exceed 0.70, as supported by our study. Outer loadings and AVE are employed to assess convergent validity. Kock [71] proposed that a loading value of 0.70 or higher is acceptable. This outcome indicates a variation of more than 50% in the indicator, which ensure reliability of a satisfactory item. Furthermore, Table 4 shows that all outside loading values exceed 0.70. According to Hair et al. [73], the standard threshold of all AVEs must be above 0.50 for convergent validity. Table 4 found that the AVE values are between 0.54 and 0.76, which are above the standard level. All this investigate ensure that there are no absence issues regarding convergent validity (refer to Fig. 2).

To test the discriminant validity, Tables 5 and 6 used the Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT). The Fornell-Larcker Criter, as demonstrated in Table 5, exceeds the correlations between the diagonal constructs and the other off-diagonal constructs, ensuring appropriate discriminant validity [74]. Hair et al. [73] also proposed that the HTMT value should be below 0.90. According to Table 6, the HTMT outputs indicate that all values are below 0.90, which is deemed satisfactory. Consequently, all constructs validate discriminant validity.

Table 3 Descriptive statistics

Descriptive statistics			
Construct	**N**	**Mean**	**Std. deviation**
Information quality (IFQ)	640	3.96	0.75
Interaction quality (ITQ)	640	3.91	0.86
Perceived usefulness (PU)	640	3.75	0.83
Perceived ease of use (PEU)	640	3.85	0.79
Attitude (ATT)	640	4.14	0.78
ChatGPT adoption (CGPTA)	640	3.88	0.83
System quality (SQ)	640	3.86	0.75
Social influence (SI)	640	3.96	0.58
Valid N (listwise)	640		

Table 4 Test of internal consistency and convergent validity

Constructs	Items	Outer loadings	Cα	CR (rho_a)	CR (rho_c)	AVE
Attitude (ATT)	ATT1	0.87	0.90	0.90	0.93	0.76
	ATT2	0.89				
	ATT3	0.88				
	ATT4	0.85				
ChatGPT adoption (CGPTA)	CGPTA1	0.83	0.87	0.87	0.91	0.71
	CGPTA2	0.88				
	CGPTA3	0.86				
	CGPTA4	0.80				
Information quality (IFQ)	IFQ1	0.90	0.87	0.88	0.91	0.72
	IFQ2	0.84				
	IFQ3	0.79				
	IFQ4	0.86				
Interaction quality (ITQ)	ITQ1	0.84	0.87	0.87	0.91	0.71
	ITQ2	0.83				
	ITQ3	0.89				
	ITQ4	0.81				
Perceived ease of use (PEU)	PEU1	0.83	0.90	0.90	0.93	0.72
	PEU2	0.86				
	PEU3	0.88				
	PEU4	0.85				
	PEU5	0.81				
Perceived usefulness (PU)	PU1	0.88	0.89	0.89	0.92	0.70
	PU2	0.85				
	PU3	0.84				
	PU4	0.85				
	PU5	0.75				
Social influence (SI)	SI1	0.94	0.87	0.87	0.89	0.54
	SI2	0.93				
	SI3	0.91				
	SI4	0.92				
System quality (SQ)	SQ1	0.76	0.83	0.83	0.89	0.66
	SQ2	0.86				
	SQ3	0.81				
	SQ4	0.82				

3.9 Assessing structural model

Figure 3 shows the structured model of this research. To test the model, 10,000 bootstrap subsamples were used with a two-tailed test for the bias-corrected percentile approach [73].

As proposed by [75], our test results of the R^2. The endogenous variable has a value of 0.91, as shown in Table 7, indicating a high level of precision for the model.

Concerning each construct's performance, the importance-performance map analysis (IPMA) broadens the PLS-SEM results [76]. Table 8 indicates that ATT is particularly crucial for demonstrating the aim construct of CGPTA. An increase of one unit in ATT's importance enhances CGPTA's performance by the entire effect of ATT on CGPTA, quantified as 0.47. The performance of ATT is also notably high, making the foundational feature of this architecture particularly relevant for managerial operations. Given the subpar importance of PU, its performance is low; there exists considerable potential for enhancement (Fig. 4).

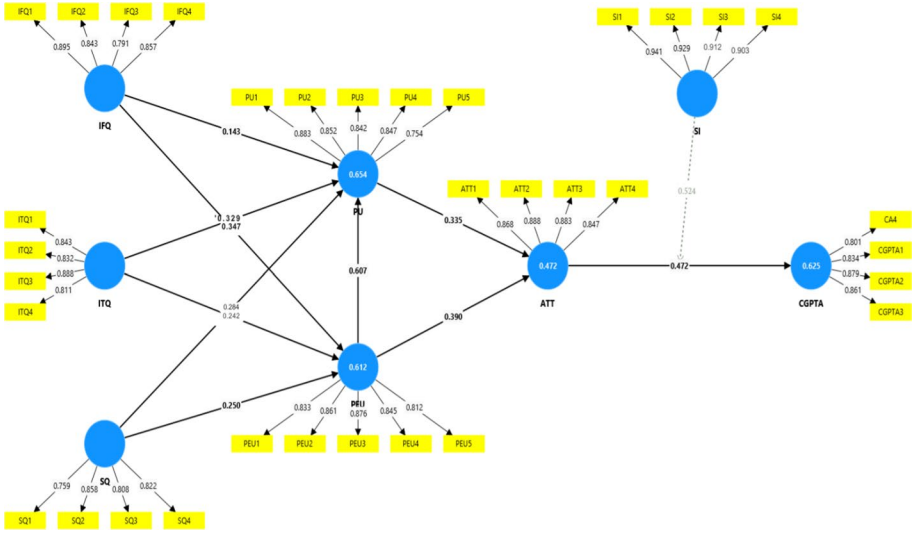

Fig. 2 Measurement model

Table 5 Results of Fornell-Larcker criteria

Construct	ATT	CGPTA	IFQ	ITQ	PEU	PU	SI	SQ
ATT	0.87							
CGPTA	0.73	0.84						
IFQ	0.79	0.75	0.85					
ITQ	0.85	0.77	0.79	0.84				
PEU	0.66	0.74	0.74	0.72	0.85			
PU	0.65	0.79	0.68	0.66	0.79	0.84		
SI	0.67	0.72	0.71	0.73	0.70	0.68	0.68	
SQ	0.73	0.73	0.80	0.80	0.72	0.65	0.67	0.81

Table 6 Results of HTMT

Construct	ATT	CGPTA	IFQ	ITQ	PEU	PU	SI	SQ
ATT								
CGPTA	0.81							
IFQ	0.79	0.85						
ITQ	0.75	0.88	0.82					
PEU	0.73	0.85	0.83	0.81				
PU	0.71	0.80	0.76	0.74	0.88			
SI	0.81	0.87	0.87	0.89	0.82	0.82		
SQ	0.84	0.85	0.84	0.85	0.84	0.75	0.87	

Bootstrapping was used to examine the construct's path coefficient. As reported by Hair et al. [75], a P-value of less than 0.05 is reliable, while it is deemed 1.96 for the critical value for T-statistics of a two-tailed test. Table 9 indicates that the t-values and p-values for all hypotheses meet the prescribed criteria. Consequently, all the hypotheses were affirmed. Hair et al. [77] also suggested that the path coefficient is significant at the 0.05 level if the 95% confidence interval excludes 0. In Table 9, zero is not considered between any of the relationships.

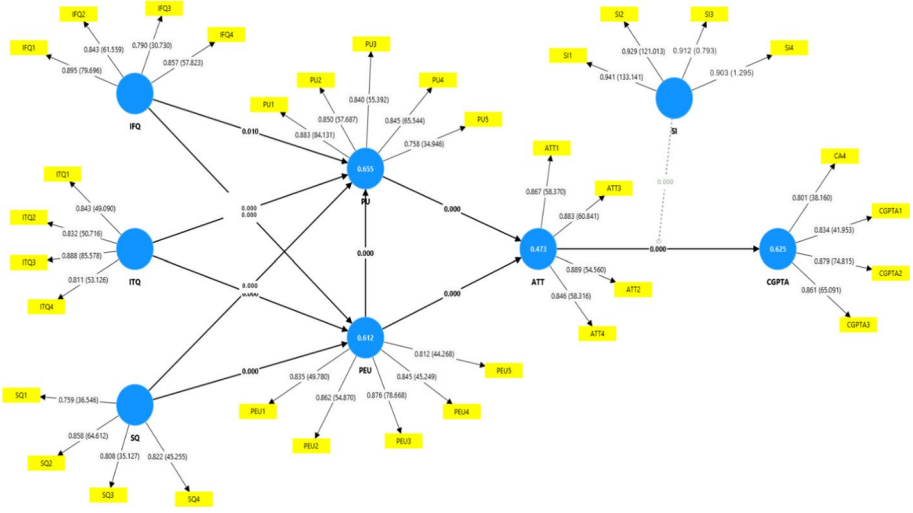

Fig. 3 Structural model

Table 7 Results of the coefficient of determination (R^2)

	R-square	R-square adjusted
ChatGPT adoption (CGPTA)	0.63	0.62

Table 8 IPMA results full data set

ChatGPT adoption (CGPTA)		
Latent variable	**Total effect (importance)**	**Index value (performance)**
Attitude (ATT)	0.47	78.42
Information quality (IFQ)	0.12	74.10
Interaction quality (ITQ)	0.08	72.92
Perceived ease of use (PEU)	0.28	71.34
Perceived usefulness (PU)	0.16	69.21
Social influence (SI)	0.42	72.61
System quality (SQ)	0.07	71.65

3.10 Necessary condition analysis (NCA)

Furthermore, the relationship between the exogenous variables (IFQ, ITQ, PU, PEU, ATT, and SQ) and SI is examined using the Necessary Condition Analysis (NCA). Dul first introduced the NCA method in 2016 and integrated it into SmartPLS V4. SmartPLS 4.0 was used to analyze our study following the latent variable scores. NCA essentially facilitates understanding the conditions set by the independent variables necessary for the occurrence of the dependent variables [78]. In NCA, the necessity effect size d with its statistical significance defines the need of a variable or construct for specific conditions, with d values extending from 0 to 1 ($0 \le d \le 1$) [79]. suggested that a small, medium, large, and very large effect size is when the NCA values are $0 < d < 0.1$, $0.1 \le d < 0.3$, $0.3 \le d < 0.5$, and $d \ge 0.5$, respectively. Despite the effect size assessment [80], also suggested evaluating the evidence against the null hypothesis, particularly through an "approximate permutation test" to estimate the exact p-value and prevent Type 1 errors and false-positive conclusions. In Table 10, we see that the effect size ranged from 0.22 to 0.40 in our analysis. SI demonstrates medium effects of predictor variables on CGPTA. Other constructs show a large effect. The effect size of this study's variables was

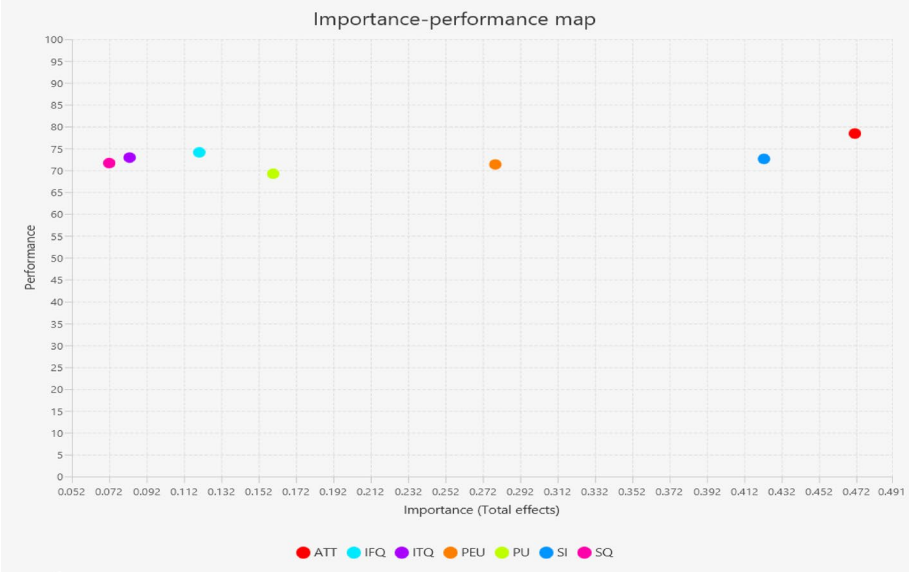

Fig. 4 Importance-performance map (constructs)

Table 9 Results of path co-efficient and confidence interval test

Hypothesis	Path co-efficient				Confidence interval		Decision
	Path	Original sample (O)	T statistics	*P* values	5%	95%	
Direct effect							
H_1	IFQ -> PU	0.15	2.58	0.01	0.04	0.26	Supported
H_2	IFQ -> PEU	0.35	5.69	0.00	0.23	0.47	Supported
H_3	ITQ -> PU	0.16	2.76	0.00	0.13	0.21	Supported
H_4	ITQ -> PEU	0.24	4.88	0.00	0.14	0.34	Supported
H_5	SQ -> PEU	0.25	4.65	0.00	0.15	0.36	Supported
H_6	SQ -> PU	0.22	4.54	0.00	0.07	0.11	Supported
H_7	PEU -> PU	0.61	11.85	0.00	0.50	0.70	Supported
H_8	PU -> ATT	0.34	6.20	0.00	0.23	0.44	Supported
H_9	PEU -> ATT	0.39	7.62	0.00	0.29	0.49	Supported
H_{10}	ATT -> CGPTA	0.47	8.80	0.00	0.36	0.57	Supported
Moderation effect							
H_{11}	SI x ATT -> CGPTA	0.18	2.87	0.00	0.12	0.22	Supported

Table 10 Ceiling line effect size (CE-FDH)

Constructs	Original effect size	95%	Permutation *p*-value
Attitude (ATT)	0.31	0.03	0.00
Information quality (IFQ)	0.30	0.03	0.00
Interaction quality (ITQ)	0.30	0.02	0.00
Perceived ease of use (PEU)	0.36	0.02	0.00
Perceived usefulness (PU)	0.32	0.02	0.00
Social influence (SI)	0.22	0.02	0.00
System quality (SQ)	0.40	0.05	0.00

further confirmed by using the permutation test with p-values. All the permutation values are found to be significant ($p < 0.05$) (Fig. 5).

The suggested ceiling line is utilized to condone signaling extraneous linear assumptions in predictors with outcome variables. The ceiling line gives an assumption to

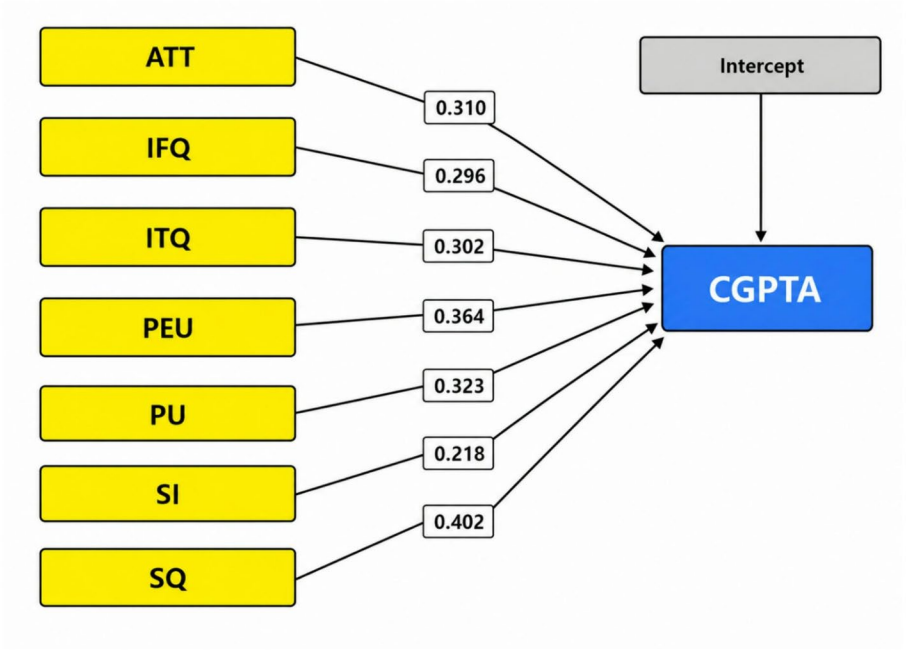

Fig. 5 Ceiling line effect size

assess whether any specific condition restricts the outcome of the analysis [81]. According to Dul [79], the ceiling lines are of two types: Ceiling Envelopment – Free Disposal Hull (CE-FDH) and Ceiling Regression – Free Disposal Hull (CR-FDH). The CE-FDH is applied for discrete data or data with few levels, whereas the CR-FDH is employed for continuous data. Grounded in the characteristics of our data, this study employed the Envelopment-Free Disposal Hull (CE-FDH) line. Figure 6 affirms that the ceiling line affirms a specific level of CGPTA, demonstrating the required level of a particular predicting variable [82].

Finally, Table 11 exhibits the overall outputs from both the logic and necessity perspectives. According to Table 11, all the paths are significant in the PLS-SEM analysis. NCA parameters also indicate that all of the paths are both meaningful ($0 \leq d \leq 1$) and significant ($p < 0.05$) necessary conditions for robust ChatGPT Adoption. On average, an increase in the ATT, IFQ, ITQ, PEU, PU, SI, and SQ will lead to improved ChatGPT Adoption.

4 Discussion

This study explores the use of ChatGPT among Bangladeshi university students and its impact on their satisfaction. It develops 11 hypotheses with 8 variables. The findings confirmed all hypotheses as well as the moderating role of SI as significant and conclusive. This study offers valuable insights to the stakeholders to improve the efficiency and user experience of AI tools like ChatGPT. Our results do not just reveal the number of data points, but also reveal a deeper meaning of our theoretical framework (Integrated Framework). In the traditional TAM or DeLone & McLean model, technology adoption is viewed as a single or individual decision. But our results demonstrate that in a collectivist culture like Bangladesh, system quality is only effective when it is certified by social influence. This challenges previous Western and individualistic research and

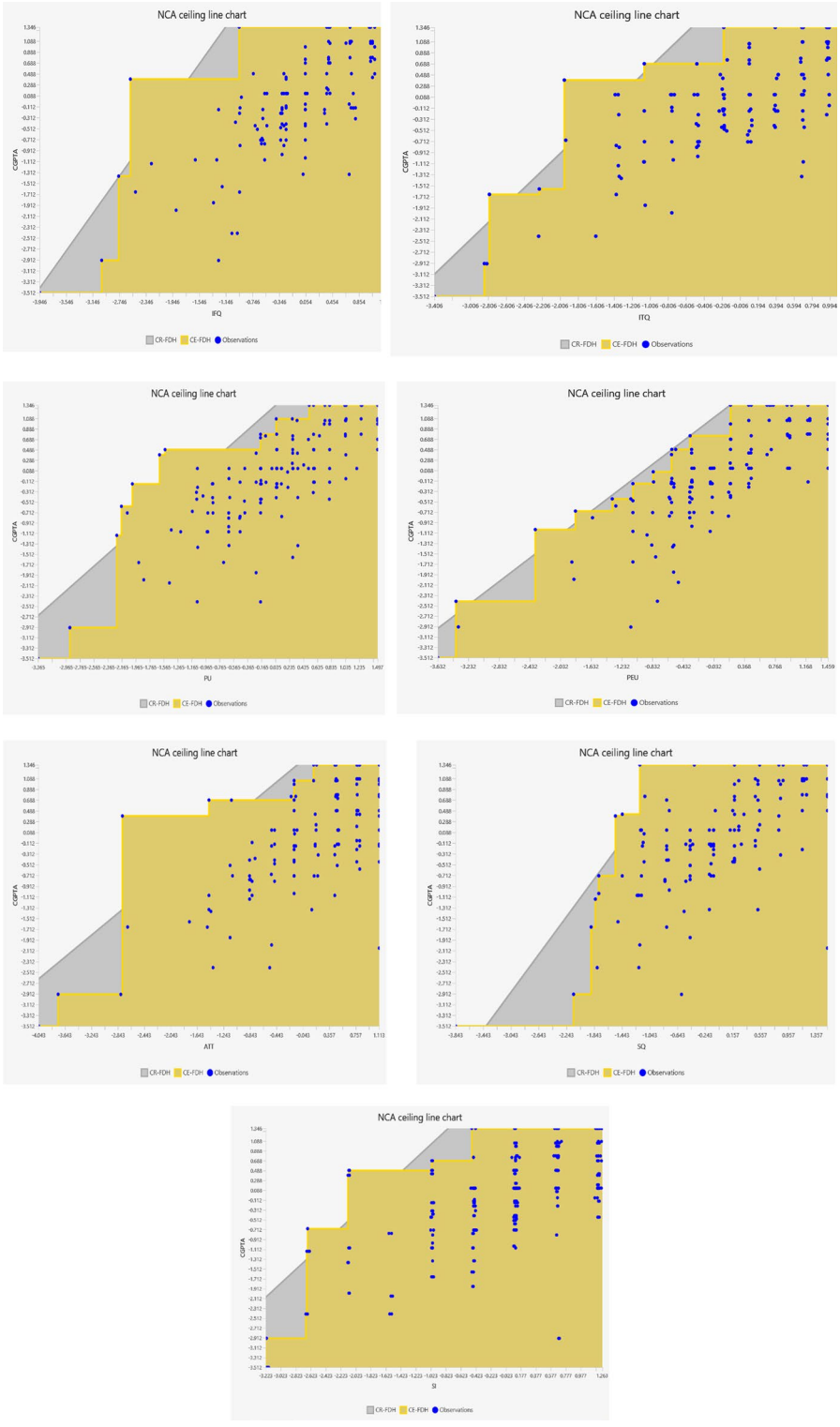

Fig. 6 NCA ceiling line chart

demonstrates that the use of AI technology in emerging economies is not just a technical decision, but a socially constructed process.

Firstly, the significant combination between IFQ and PU indicates that users feel more comfortable using ChatGPT when they find standard information that meets their

Table 11 Necessity and sufficiency results – ChatGPT Adoption (CGPTA)

PLS-SEM -Significance analysis path				Necessary condition analysis (NCA)			
Hypothesis	**Path coefficient**	**P value**	**Sufficiency**	**Path**	**Effect size (d-value)**	**P value**	**Necessary condition**
IFQ -> PU	0.15	0.01	Fulfilled	ATT -> CGPTA	0.31	0.00	Fulfilled
IFQ -> PEU	0.35	0.00	Fulfilled	IFQ -> CGPTA	0.30	0.00	Fulfilled
ITQ -> PU	0.16	0.00	Fulfilled	ITQ -> CGPTA	0.30	0.00	Fulfilled
ITQ -> PEU	0.24	0.00	Fulfilled	PEU -> CGPTA	0.36	0.00	Fulfilled
SQ -> PEU	0.25	0.00	Fulfilled	PU -> CGPTA	0.32	0.00	Fulfilled
SQ -> PU	0.22	0.00	Fulfilled	SI -> CGPTA	0.22	0.00	Fulfilled
PEU -> PU	0.61	0.00	Fulfilled	SQ -> CGPTA	0.40	0.00	Fulfilled
PU -> ATT	0.34	0.00	Fulfilled				
PEU -> ATT	0.39	0.00	Fulfilled				
ATT -> CGPTA	0.47	0.00	Fulfilled				
SI x ATT -> CGPTA	0.18	0.00	Fulfilled				

requirements [11]. also found the same result: that standard information enhances a system's PU. High IFQ (frequent, informative, accurate, pertinent, and straightforward responses) plays a major contribution to technology adoption [83]. High IFQ enhances ChatGPT effectiveness, including class work, learning new topics, and overall improving the productivity of Bangladeshi university students who rely on self-learning and need academic help [84]. In situations where getting formal academic help is scarce, a high level of IFQ enhances ChatGPT's perceived and real utility.

Secondly, the findings of this study indicate a positive and significant nexus between IFQ and PEU. Yu et al. [83] It has also been investigated that if technology provides accurate, pertinent, and standardized information, people feel more comfortable adopting it. They also found that high IFQ in the scope of ChatGPT indicates that it is user-friendly and provides trustworthy data and feedback. As Bangladeshi university students have limited access to in-person academic support or learning materials, such a relationship is effective for them. Won et al. [85] contend that various opinions about utilizing branded sports applications will be influenced by information quality, which is a system-oriented trait. Users are more likely to find the branded sports app user-friendly, practical, and entertaining when they believe the content and system are of high quality. As a result, the following theories are proven.

Thirdly, the significant relationship between ITQ and PU indicates that when users use ChatGPT, it increases their level of responsiveness and makes them more interactive, which ultimately enhances work performance. Both responsiveness and interactivity are components of ITQ. Logical engagement and an effective conversational flow can upgrade the mindset of an AI tool's competence, where ITQ plays a crucial role through its internal evaluation process [10]. As AI dramatically changes IT efficiency and the way of education, Bangladesh should accept ITQ in its IT and education industries. For beginners, AI tools must be user-friendly and easy to access; otherwise, they may feel bored [86].

Fourthly, when AI tools become responsive and intuitive interfaces, they will be user-friendly, and ITQ greatly influences PEU. AI services, such as aiding and understanding

the context, save users time, which ultimately makes the system user-friendly [11]. Whether users adopt technology or deny it totally depends on system design and user experience [87]. Petter et al. [88] also found the same result. In order to get maximum advantage from AI, Bangladesh must promote PEU in all possible sectors. This is because user-friendly AI and simplified interactions motivate academicians to close digital literacy gaps and invest in infrastructure [89].

Fifthly, the significant relationship between SQ on PU and PEU indicates that SQ has a significant contribution to creating a favourable mindset toward ChatGPT. Similarly, Alshurideh et al. [35] found that SQ is a key contributor in terms of measuring a system's efficiency and the level of benefits which students perceive about the system. Furthermore, Alkhawaja et al. [38] also investigated that SQ has a substantial influence on how people think about an AI tool and how exactly they are to use it. Technical issues and other difficulties may be the key obstacles for users to use e-learning systems; such situations greatly motivate people to use AI tools [40]. However, recent studies conducted by Fitria et al. [41] revealed that there is a positive relationship between SQ and PEU in e-learning systems.

Sixthly, the substantial influence of PU on ATT indicates that end users' positive sentiment toward AI tools, including ChatGPT, has been influenced by the mindset of their usefulness. When people think their AI tools significantly help their duties, their emotional and behavioural reactions are also enhanced [90]. A recent study in Bangladesh has found that PU has a substantial contribution to users' perception regarding technology [91]. Moreover, it also found that practical value is the main influencing element to adopt AI tools. In addition, Emon et al. [92] also found that people are more likely to use AI tools when AI increases its productivity and ultimately stimulates people to adopt it in Bangladesh.

Seventhly, there is a positive correlation between PEU and ATT. Users belong to a positive mindset regarding AI tools, including ChatGPT, when they find them easily accessible and user-friendly [93]. New learners feel less annoyance and prolonged engagement when they find tools more user-friendly [94]. Such types of facilities are urgent in Bangladesh, particularly in the nation's diverse digital sectors, and such initiatives stimulate people to use more technology in their day-to-day activities [95].

Eighthly, the relationship between ATT and CA indicates that ChatGPT enhances the possibility of adopting more AI tools in different sectors, including education [96]. Furthermore, Shahzad et al. [33] discovered that prior perceptions of ChatGPT's utility and usability significantly influenced ATT, which in turn encourages students to utilize it for academic reasons. This study found that positive perception toward technology is the sine qua non for increasing users' involvement. For example, a positive mindset toward AI products can increase users' level of confidence to get involved with AI permanently in Bangladesh. It is paramount for stimulating digital technology and successfully integrating AI into different sectors, including education, in Bangladesh [97].

Ninthly, the moderating role of SI is significant in this study. In Bangladesh, users feel more comfortable using AI tools, including ChatGPT, based on both personal preferences and firsthand experiences. In addition, social influence from ongoing trends or initial social endorsement may stimulate users to adopt technology [98]. This is a notable sign for future transformation plans, which emphasise that the inherent value and user experience of AI innovation, as well as SI, act as key factors for long-term adoption and

consumer satisfaction [99]. According to [60], friends, colleagues, online communities, social trends, and other factors are examples of SI. Early users' positive mindset, feedback, stories, and endorsement stimulate others to understand ChatGPT's benefits and develop a culture that promotes the pack of technology users [10]. argued that university teachers who use ChatGPT reported more institutional support (high SI). Adoption was more likely to have a positive effect when social norms and leadership support were high.

Finally, to analyze the main empirical results of this study in depth, it is essential to make a critical comparison with the work of Almulla (2024) [16]; because his work served as the main foundation for our integrated model. Almulla (2024) [16] successfully demonstrated the effectiveness of integrating system and quality parameters with Technology Acceptance Model (TAM) in the context of smart learning. Consistent with his findings, our study also confirms that IFQ is a very important driver of PU and ITQ significantly enhances PEU among higher education students. However, our study has uncovered several new findings that add new dimensions beyond the original framework of Almulla (2024) [16]. Almulla's model primarily focused on direct cognitive and systems-centered pathways, but there was limited attention to social and cultural influences. Our study advances the theoretical understanding of AI adoption by adding the moderating role of SI in a developing South Asian educational ecosystem like Bangladesh. Our data demonstrate that the positive relationship between students' ATT and CGPTA is further strengthened by social and peer support. In a digital economy in transition, technology adoption is not a single or isolated mental process driven by the quality of the system, but rather a socially constructed one. In a country with a collective learning culture like Bangladesh, peer motivation and institutional support act as a catalyst, amplifying the direct pathways identified in model of Almulla [16]. As a result, by incorporating these multidimensional aspects, this study significantly improves the theoretical coherence of the DeLone & McLean IS Success Model and TAM and demonstrates that social structure is a very important condition for the adoption of artificial intelligence in higher education.

4.1 Theoretical implications

The outcomes of our study have numerous theoretical significances. The objective of this study is to fill knowledge gaps and develop current understanding by including IFQ, ITQ, and SQ into the TAM framework. ITQ has a significant contribution in this study, which concentrates on measuring the level of user satisfaction through analysing data produced by AI systems, including ChatGPT, based on IFQ dimensions. The development of AI generative tools, including ChatGPT, poses a significant threat in terms of guaranteeing the calibre of dynamically created materials. To confirm that these AI tools successfully fulfil customers' information needs, it is crucial to recheck the conventional parameters, including correctness, relevance, and completeness. In addition, ChatGPT has calibre in the learning process, but there is a growing concern regarding false information and ethical issues. However, this study provides a real position of generative AI by measuring the calibre of the data it produced. The mindset of companies toward information and interaction may bring a large-scale change in companies' strategy. This shift stimulates people to understand the data and use it as a supportive tool in their own decisions. As this study provides insightful knowledge about the widespread use of

AI language models, it is crucial to be aware of the result rather than rely on the cause and effect of the result. Researchers always found interesting results from ChatGPT; that's why they need to explore and examine a large amount of material. Sometimes it becomes handy for academicians to accumulate large amounts of information, provide feedback, and write theses and reports. As an automated computer program, it is interactive, which makes AI learning easier for users and those in academia. This study carefully emphasises the contribution of social influence in ChatGPT adoption and provides current information and trends in other situations based on analysing studies. Students set a positive mindset to use ChatGPT, and this perceived usefulness influences them to adopt new technology. According to this relationship, students are more likely to use technology in their academic habits the more they recognise its benefits. Research can help policymakers ensure that new teaching methods are used responsibly without compromising how well they are.

4.2 Practical implications

Numerous implications for companies and the global society will result from the current study. First, several elements outlined in the report will increase the general public's access to technology. In an educational setting, the factors that create positive behavioural intention to use this tool are its utility, social presence, credibility, enjoyment, and incentive. People would continue to seek AI help for solutions, which would lead to an increase in literacy and general awareness because this research highlights the tool's value for education and learning. This will have a profound effect on how human brains learn and evolve since computer contact provides more thorough information. Secondly, the users' motivation during ChatGPT interactions is highly positive. At the same time, users are beginning to believe that the bot's response is reliable. Technology has gained a lot of traction and is being discussed in social contexts both online and offline. Students feel comfortable utilising this tool as a result. Our study's findings about these traits can potentially help communities outside of students. Third, universities and colleges will be able to produce skilled graduates that employers want. ChatGPT would be a powerful tool to stimulate productivity and motivate adaptive learning through repetitive chores and upgrading students' learning experiences. Fourth, it is necessary to consider that social influence has a significant impact on students' adoption intention. It is an inherited characteristic of human beings to take advice from peers, particularly when people face new things such as cutting-edge technology. By developing systems that motivate users to have natural discussions about AI technologies, universities would gain an advantage in this regard. Different types of platforms provide students access to use ChatGPT, where they can share stories, endorsements, or sometimes difficulties. Fifth, more specifically, within the context of developing and collectivistic educational ecosystems like Bangladesh, these findings offer highly tailored insights for local stakeholders. Since social influence is a dominant driver, university administrators and educators should move away from top-down mandates; instead, they should foster peer-led learning circles and collaborative workshops where students can collectively model ethical and productive AI usage. Furthermore, institutional policymakers must design clear, context-specific AI guidelines and robust data-handling frameworks. This is crucial to directly mitigate student anxieties regarding data privacy and academic integrity, thereby transforming conversational AI into a trusted, secure, and equity-driven

learning assistant rather than a source of institutional risk. Sixth, although it is recognised that ChatGPT and other AI-driven teaching technologies hold the leading position in organisation, it is quite impossible to successfully adopt such tools without ensuring a conducive corporate culture. Universities should take it into consideration and take effective measures to develop a comprehensive strategy. Finally, if ChatGPT were made more user-friendly and provided guidelines for people on how to use it in the beginning phase, it would be less complex, and users would find an easy way to use it and integrate it into their real lives. Therefore, it is crucial to focus on the right impact. As a result, we should concentrate on the significant impact and clear, real evidence.

5 Conclusion

The utilisation of AI in education has drastically changed conventional academic learning methods. It offers not only positive opportunities but also brings negative consequences in students' development. Utilising a quantitative approach, we examined the mindset of users and students about ChatGPT adoption. There is a lack of studies that incorporate user satisfaction and adoption attitude into a unified paradigm, particularly in the higher education context in Bangladesh. The factors that contribute to adopting AI tools, including ChatGPT, and their positive and negative consequences on students' level of satisfaction have gained significant attention in Bangladesh, as it pays more attention to transforming traditional education methods into digital means. This study aims to find out the key factors that motivate students to adopt ChatGPT and stimulate students' sense of happiness among Bangladeshi university students, and examine the moderating role of social influence, and ultimately fulfil this research gap. Although ChatGPT has crucial theoretical understanding in AI technologies, learning is needed to connect with the real world and practical applications. The correlation between adoption intention and knowledge application brings strong confidence for educators to use their imaginations. Schools can adopt ChatGPT-focused programmes such as presentations, case studies, assignments, and so on, so that they can engage with ChatGPT to fix their practical problems. Universities may be greatly influenced by the students' mindset towards ChatGPT. Although the cross-sectional nature of the data requires caution regarding absolute causality, the structural equation modeling (SEM) results demonstrate robust predictive relationships and direct pathways among the hypothesized constructs, deeply rooted in established technology acceptance theories. Therefore, conducting further research based on this study ought to be prudent and amenable.

5.1 Limitations and future research directions

This study offers comprehensive theoretical and practical contributions; however, there are some untouched parts that need to be addressed by future academicians. A notable constraint of this study is the reliance on purposive sampling, a non-probability technique chosen due to the lack of an official, centralized database of AI-using university students in Bangladesh. While this approach was necessary to ensure that all respondents possessed genuine, active experience with ChatGPT to accurately measure the integrated success constructs, it naturally restricts statistical generalizability. Consequently, the empirical findings of this research should be interpreted with caution when applying them to the broader, non-user student population or distinct socio-economic and geographical demographics within Bangladesh or in other developing contexts. To

overcome this limitation, future research should endeavor to employ probability sampling methods across highly diversified, multi-regional university networks to broaden the generalizability and global validity of these acceptance dynamics. In this technological era, ChatGPT and OpenAI platforms have received a high level of response from global users, so it is significant to measure how these tools develop over time. Additionally, it is crucial to measure whether such tools bring positive outcomes for students, whether they improve pupils' level of learning, or whether they make them reliant on technology. Is it detrimental or benevolent for the users? Does ChatGPT have a superior quality to change the way people look for information? These are the untouched areas that academicians can explore. Although this study provides some very important results, it has some methodological limitations that pave the way for future research. Although our sample size of 640 respondents is very powerful and adequate according to standard guidelines [100] for structural equation modeling (SEM), the data are based on a cross-sectional design. This captures student attitudes at a specific point in time, making it difficult to confirm long-term causal relationships or trends. Future research should conduct longitudinal studies to track how student behavior changes as ChatGPT or generative AI technology changes. Moreover, his data is primarily based on universities in Bangladesh. To increase its generalizability, future research could include cross-cultural comparisons between developing countries in South Asia and countries with advanced digital economies. Additionally, the effects of ChatGPT use on students, academicians, and researchers may be investigated at educational institutions, colleges, or other comparable organisational contexts. Even though ethical issues might be crucial to the adoption purpose, we failed to include them. To ensure data validity and reliability, future researchers should be concerned about ethical considerations, especially in the scope of AI-driven technologies. Another limitation of this study relates to the demographic makeup of the respondents. The sample was unevenly distributed among various university types and academic disciplines. Specifically, a higher proportion of respondents attended public universities, while students from private and national universities were less represented. Additionally, the sample mainly focused on Business, Engineering, and Information Technology fields, with fewer students from Social Science and Humanities. This uneven distribution could restrict the applicability of the findings to the wider population of Bangladeshi university students. Since students from different types of institutions and academic backgrounds may have varying levels of exposure to ChatGPT, digital learning tools, academic writing, and technology acceptance, the results should be interpreted carefully. Future research should aim for a more balanced or stratified sampling method to achieve better representation across university types and disciplines. Additionally, our model explains a significant portion of the variance in ChatGPT adoption among Bangladeshi university students—evidenced by an R-squared value of 0.63—about 37% of the variance remains unaccounted for. This indicates that other relevant factors not included in the current model may also impact students' adoption of ChatGPT. Such factors could include digital literacy, institutional support, prior AI experience, perceived academic risks, trust in AI-generated information, internet access, and individual motivation to learn. Therefore, future research could enhance the model by including additional psychological, technological, institutional, and contextual variables to better explain ChatGPT adoption in higher education. Additionally, a notable boundary condition of this study is that data collection was

restricted exclusively to participants with prior experience using ChatGPT. By focusing entirely on active users to evaluate the integration of system quality metrics and cognitive acceptance, the theoretical model naturally captures the drivers of post-adoption behavior and user satisfaction rather than the barriers to initial entry. Consequently, the perspectives of non-adopters, such as students facing digital literacy gaps, technological anxiety, privacy concerns, or institutional resistance remain unexamined. This limits the model's capacity to comprehensively map out the hurdles to initial AI adoption across the broader student body. To address this, future research should intentionally employ a comparative framework that incorporates both adopters and non-adopters, thereby providing a more holistic understanding of user resistance and pre-adoption barriers in higher education. Finally, It is important to note that student satisfaction with ChatGPT is not solely driven by positive quality metrics. In reality, students continually weigh these benefits against negative dimensions such as AI hallucinations (false information) and ethical anxieties. Even when social influence accelerates adoption, underlying worries about data privacy and academic integrity remain active background constraints in the higher education landscape.

Author contributions
K.N. conceptualized the study and contributed to research design. K.O.S. and M.A.A.M. developed the methodology and supervised data analysis. S.C. conducted the literature review and assisted with data curation. F.R. contributed to data collection and validation. U.H.A. supported formal analysis and interpretation of results. S.A. contributed to writing—review and editing. T.T. led the original draft preparation, coordinated the research process, and managed correspondence.

Funding
Not applicable.

Data availability
The data generated and analyzed in this study are available from the corresponding author upon request.

Declarations

Ethics approval and consent to participate
Ethical approval for this study was obtained from the Research Ethics Committee (REC) of Port City International University, Bangladesh (Reference No. PCIU/rCell/ES 26 03/02 01 (01)). All procedures involving human participants were conducted in accordance with the relevant institutional and national ethical standards, the principles of the Declaration of Helsinki, and all applicable regulations. Informed consent was obtained from all participants prior to their participation in the study. Participants were fully informed about the purpose of the research, and their participation was voluntary.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Author details
[1]Department of Business Administration, Presidency University, Dhaka 1212, Bangladesh
[2]Department of Management Studies, Comilla University, Comilla, Bangladesh
[3]Green Business School, Green University of Bangladesh, Narayanganj, Dhaka, Bangladesh
[4]Department of Information Science and Library Management, University of Rajshahi, Rajshahi 6205, Bangladesh
[5]Uttara University, Dhaka 1230, Bangladesh
[6]Department of Business Administration, Port City International University, Chattogram 4000, Bangladesh
[7]Department of Business Management, North China University of Water Resources and Electric Power, Zhengzhou 450046, China
[8]Department of Marketing, University of Chittagong, Chittagong 4331, Bangladesh
[9]Department of Finance, University of Chittagong, Chittagong 4331, Bangladesh

Received: 2 March 2026 / Accepted: 19 August 2026
Published online: 24 September 2026

References

1. Mun IB, Hwang KH. Understanding ChatGPT continuous usage intention: The role of information quality, information usefulness, and source trust. Inform Dev. 2025;41(3):675–91.

2. Legramante D, Azevedo A, Azevedo JM. Integration of the technology acceptance model and the information systems success model in the analysis of Moodle's satisfaction and continuity of use. Int J Inform Learn Technol. 2023;40(5):467–84. https://doi.org/10.1108/ijilt-12-2022-0231.
3. Balaskas S, Tsiantos V, Chatzifotiou S, Rigou M. Determinants of ChatGPT Adoption Intention in Higher Education: Expanding on TAM with the Mediating Roles ofTrust and Risk. Information. 2025;16(2):82. https://doi.org/10.3390/info16020082.
4. Lai CY, Cheung KY, Chan CS. Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: An extension of the technology acceptance model. Computers Education: Artif Intell. 2023;5:100178.
5. Almogren AS, Al-Rahmi WM, Dahri NA. Exploring factors influencing the acceptance of ChatGPT in higher education: A smart education perspective. Heliyon. 2024;10(11):e31887. https://doi.org/10.1016/j.heliyon.2024.e31887.
6. Jo H. Decoding the ChatGPT mystery: a comprehensive exploration of factors driving AI language model adoption. Inform Dev. 2023.
7. Tiwari CK, Bhat MA, Khan ST, Subramaniam R, Khan MAI. What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT. Interact Technol Smart Educ. 2024;21(3):333–55.
8. Davis FD, Granić A, Marangunić N. The technology acceptance model: 30 years of TAM. Switzerland: Springer International Publishing AG; 2024.
9. Mahmud A, Sarower AH, Sohel A, Assaduzzaman M, Bhuiyan T. Adoption of ChatGPT by university students for academic purposes: Partial least square, artificial neural network, deep neural network and classification algorithms approach. Array. 2024;21:100339. https://doi.org/10.1016/j.array.2024.100339.
10. Barakat M, Salim NA, Sallam M. University educators perspectives on ChatGPT: A technology acceptance model-based study. Open Praxis; 2025.
11. Davis FD. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Q. 1989;13(3):319. https://doi.org/10.2307/249008.
12. DeLone WH, McLean ER. Information Systems Success: the Quest for the Dependent Variable. Inform Syst Res. 1992;3(1):60–95. https://doi.org/10.1287/isre.3.1.60.
13. Çelik K, Ayaz A. Validation of the Delone and McLean information systems success model: a study on student information system. Educ Inform Technol. 2022;27(4):4709–27. https://doi.org/10.1007/s10639-021-10798-4.
14. Gürkut C, Nat M. Important Factors Affecting Student Information System Qualityand Satisfaction. EURASIA J Math Sci Technol Educ. 2017;14(3). https://doi.org/10.12973/ejmste/81147.
15. DeLone WH, McLean ER. The DeLone and McLean model of information systems success: a ten-year update. J Manage Inform Syst. 2003;19(4):9–30.
16. Almulla MA. Investigating influencing factors of learning satisfaction in AI ChatGPT for research: university students perspective. Heliyon. 2024. https://doi.org/10.1016/j.heliyon.2024.e32220.
17. Kibria MG, Khanom K, Sultana J, Chowdhury FP. Determinants of ChatGPT adoption in higher education: an empirical study on Public and Private University Students in Bangladesh. Global Bus Rev. 2026. https://doi.org/10.1177/09721509261443740.
18. Pikhart M, Al-Obaydi LH. Reporting the potential risk of using AI in higher Education: Subjective perspectives of educators. Computers Hum Behav Rep. 2025;18:100693. https://doi.org/10.1016/j.chbr.2025.10069.
19. Karahan Adalı G, Bilgili A. Generative AI in Higher Education: Students' Perspectives on Adoption, Ethical Concerns, and Academic Impact. Acta Infologica. 2025;9(1):147–66. https://doi.org/10.26650/acin.1670197.
20. Lawaju P, Adhikari SU, Devkota J. Impact of AI in Education: An Evidence from Use of ChatGPT in Management Education in Nepal. Quest J Manage Social Sci. 2024;6(3):621–42.
21. Zemedkun MA. The influence of parental attitude on the self-esteem of students with visual impairment in selected middle schools of Dessie city, Ethiopia. Discover Educ. 2026. https://doi.org/10.1007/s44217-026-01147-z. Advance online publication.
22. Holsapple CW, Lee-Post A. Defining, Assessing, and Promoting E-Learning Success: An Information Systems Perspective*. Decis Sci J Innovative Educ. 2006;4(1):67–85. https://doi.org/10.1111/j.1540-4609.2006.00102.x.
23. Rahmadani A. Family language policy and translanguaging practices as support for language development in early childhood students with autism spectrum disorder in Indonesia. Discover Educ. 2026. https://doi.org/10.1007/s44217-026-01149-x. Advance online publication.
24. Legramante D, Azevedo A, Azevedo JM. Integration of the technology acceptance model and the information systems success model in the analysis of Moodle's satisfaction and continuity of use. Int J ofInformation Learn Technol. 2023;40(5):467–84. https://doi.org/10.1108/ijilt-12-2022-0231.
25. Gupta P, Prashar S, Vijay TS, Parsad C. Examining the influence of antecedents of continuous intention to use an informational app: The role of perceived usefulness and perceived ease of use. Int J Bus Inform Syst. 2021;36(2):270. https://doi.org/10.1504/IJBIS.2021.112829.
26. Tsai YY, Chao CM, Lin HM, Cheng BW. Nursing staff intentions to continuously use a blended e-learning system from an integrative perspective. Qual Quant. 2018;52(6):2495–513.
27. Li X, Zhu W. System quality, information quality, satisfaction and acceptance of online learning platform among college students in the context of online learning and blended learning. Front Psychol. 2022;13:1054691. https://doi.org/10.3389/fpsyg.2022.1054691.
28. Nyamekye E, Uwen GO, Nketsiah J, Soré WAF, Akuamah A, Mpolomoka DL. Sociopsychological predictors of students' willingness to communicate in their L1: Insights from some Anglophone African countries. Discover Educ. 2026. https://doi.org/10.1007/s44217-026-01152-2. Advance online publication.
29. Zhai X. ChatGPT User Experience: Implications for Education. SSRN Electron J. 2022. https://doi.org/10.2139/ssrn.4312418.
30. Biswas S. Role of ChatGPT in Computer Programming. Mesopotamian J Comput Sci. 2023;2023:9–15. https://doi.org/10.58496/MJCSC/2023/002.
31. Cotton DRE, Cotton PA, Shipway JR. Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations Educ Teach Int. 2024;61(2):228–39. https://doi.org/10.1080/14703297.2023.2190148.
32. Bayat M, Banihashem SK, Noroozi O. The effects of collaborative reasoning strategies on improving primary school students' argumentative decision-making skills. J Educational Res. 2022;115(6):349–58. https://doi.org/10.1080/00220671.2022.2155602.

33. Shahzad MF, Xu S, Javed I. ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. Int J Educational Technol High Educ. 2024;21(1):46. https://doi.org/10.1186/s41239-024-00478-x.
34. Eom SB, Arbaugh JB, editors. Student satisfaction and learning outcomes in e-learning: an introduction to empirical research. IGI Global. 2011. https://doi.org/10.4018/978-1-60960-615-2
35. Alshurideh MT, Salloum SA, Kurdi A, Abdel Monem B, A., Shaalan K. Understanding the Quality Determinants that Influence the Intention to Use the Mobile Learning Platforms: A Practical Study. Int J Interact Mob Technol (iJIM). 2019a;13(11):157. https://doi.org/10.3991/ijim.v13i11.10300.
36. Rui-Hsin K, Lin C-T. The usage intention of e-learning for police education and training. Policing: Int J. 2018;41(1):98–112. https://doi.org/10.1108/PIJPSM-10-2016-0157.
37. Mohammadi H. Investigating users' perspectives on e-learning: An integration of TAM and IS success model. Comput Hum Behav. 2015;45:359–74. https://doi.org/10.1016/j.chb.2014.07.044.
38. Alkhawaja MI, Halim MSA, Abumandil MS, Al-Adwan AS. System quality and students' acceptance of the e-learning system: the serial mediation of perceived usefulness and intention to use. Contemp Educational Technol. 2022. 14(2).
39. Dorobăț I, Corbea (Florea) AMI. Assessing ChatGPT Adoption in Higher Education: An Empirical Analysis. Electronics. 2025;14(23):4739. https://doi.org/10.3390/electronics14234739.
40. Ghazal S, Aldowah H, Umar I. (2018). Critical Factors to Learning Management System Acceptance and Satisfaction in a Blended Learning Environment. In F. Saeed, N. Gazem, S. Patnaik, A. S. Saed Balaid, & F. Mohammed, editors, *Recent Trends in Information and Communication Technology* (Vol. 5, pp. 688–698). Springer International Publishing. https://doi.org/10.1007/978-3-319-59427-9_71
41. Fitria F, Yahya M, Ali MI, Purnamawati P, Mappalotteng AM. The Impact of System Quality and User Satisfaction: The Mediating Role of Ease of Use and Usefulness in E-Learning Systems. Int J Environ Eng Educ. 2024;6(2):119–31. https://doi.org/10.55151/ijeedu.v6i2.134.
42. Dokhanian S, Roustapisheh N, Heidari S, Rezvani S. The Effectiveness of System Quality, Habit, and Effort Expectation on Library Application Use Intention: The Mediating Role of Perceived Usefulness, Perceived Ease of Use, and User Satisfaction. Int J Bus Inform Syst. 2022;1(1):1. https://doi.org/10.1504/IJBIS.2022.10049515.
43. Lai Y-H. The Application of Meta-Analytic SEM on Exploring Factors that Influence Teachers' Usage of Interactive Whiteboard. Pedagogical Res. 2019. https://doi.org/10.29333/pr/5854.
44. Brzustowicz R. From ChatGPT to CatGPT: the implications of artificial intelligence on library cataloging. Inform Technol Libr, 2023. https://doi.org/10.5860/ital.v42i3.16295
45. Biswas SS. Potential use of chat gpt in global warming. Ann Biomed Eng. 2023;51(6):1126–7.
46. Sadriwala MF, Sadriwala KF. Perceived usefulness and ease of use of artificial intelligence on marketing innovation. Int J Innov Digital Econ, 2022. 13(1):1-10.
47. Hasni MJS, Farah MF, Adeel I. The technology acceptance model revisited: Empirical evidence from the tourism industry in Pakistan. J Tourism Futures. 2021. https://doi.org/10.1108/JTF-09-2021-0220.
48. Hussain A, Zhiqiang M, Li M, Jameel A, Kanwel S, Ahmad S, Ge B. The mediating effects of perceived usefulness and perceived ease of use on nurses' intentions to adopt advanced technology. BMC Nurs. 2025;24(1):33. https://doi.org/10.1186/s12912-024-02648-8.
49. Najib M, Fahma F. Investigating the Adoption of Digital Payment System through an Extended Technology Acceptance Model: An Insight from the Indonesian Small and Medium Enterprises. Int J Adv Sci Eng Inform Technol. 2020;10(4):1702–8. https://doi.org/10.18517/ijaseit.10.4.11616.
50. Li K. Determinants of College Students' Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model. Sustainability. 2023;15(6):5221. https://doi.org/10.3390/su15065221.
51. Dahri NA, Yahaya N, Al-Rahmi WM, Aldraiweesh A, Alturki U, Almutairy S, Shutaleva A, Soomro RB. Extended TAM based acceptance of AI-Powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study. Heliyon. 2024;10(8):e29317. https://doi.org/10.1016/j.heliyon.2024.e29317.
52. Ahmed Dahri N, Yahaya N, Al-Rahmi M, Almuqren W, Almgren L, Alshimai AS, A., Al-Adwan S, A. The Effect of AI Gamification on Students' Engagement and Academic Achievement in Malaysia: SEM Analysis Perspectives. IEEE Access. 2025;13:70791–810. https://doi.org/10.1109/ACCESS.2025.3560567.
53. Ayalon A, Ido O. Adoption of ChatGPT in Higher Education: A UTAUT Based Comparative Study of Students and Lecturers. J Educational Technol Syst. 2026;00472395261439145. https://doi.org/10.1177/00472395261439145.
54. Sohn K, Kwon O. Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. Telematics Inform. 2020;47:101324. https://doi.org/10.1016/j.tele.2019.101324.
55. Zou M, Huang L. To use or not to use? Understanding doctoral students' acceptance of ChatGPT in writing through technology acceptance model. Front Psychol. 2023;14:1259531. https://doi.org/10.3389/fpsyg.2023.1259531.
56. Nuryakin N, Rakotoarizaka NLP, Musa HG. The Effect of Perceived Usefulness and Perceived Easy to Use on Student Satisfaction The Mediating Role of Attitude to Use Online Learning. Asia Pac Manage Bus Application. 2023;011(03):323–36. https://doi.org/10.21776/ub.apmba.2023.011.03.5.
57. Parveen K, Obidallah WJ, Phuc TQB, et al. Exploring key predictors of ChatGPT adoption in higher education: insights from UTAUT3 and ARCS model. BMC Psychol. 2026;14:397. https://doi.org/10.1186/s40359-026-04042-2.
58. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. MIS quarterly; 2003. 425–78.
59. Ayinde L, Wibowo MP, Ravuri B, Emdad FB. ChatGPT as an important tool in organizational management: A review of the literature. Bus Inform Rev. 2023;40(3):137–49. https://doi.org/10.1177/02663821231187991.
60. Etikan I, Musa SA, Alkassim RS. Comparison of convenience sampling and purposive sampling. Am J Theoretical Appl Stat. 2016;5(1):1–4. https://doi.org/10.11648/j.ajtas.20160501.11.
61. Tongco MDC. Purposive sampling as a tool for informant selection. Ethnobotany Res Appl. 2007;5:147–58. https://doi.org/10.17348/era.5.0.147-158.
62. Palinkas LA, Horwitz SM, Green CA, Wisdom JP, Duan N, Hoagwood K. Adm Policy Mental Health Mental Health Serv Res. 2015;42(5):533–44. https://doi.org/10.1007/s10488-013-0528-y. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research.
63. Aura-Tormos JI, Llacer-Martinez M, Torres-Osca I. Educational APPLICATIONS of ChatGPT in university-based dental education. A systematic review. Euro J Dental Edu. 2026;30(2):644-660. https://doi.org/10.1111/eje.70011

64. Hair JF, Hult GTM, Ringle CM, Sarstedt M. A primer on partial least squares structural equation modeling (PLS-SEM). Sage; 2014.
65. Al Mamun MA, Tanchangya T, Rahman MA, Hasan MM, Islam N, Yeamin B. Measuring the influence of fintech innovation towards consumers' attitude: Moderating role of perceived usefulness. Sustainable Futures. 2025;10:100885.
66. Tanchangya T, Al Mamun MA, Akter T, Hossain B, AbdulBaten AM, Islam N, Alam MK. Factors influencing consumers' attitudes and the moderating role of social influence in the banking industry. Discover Psychol. 2026;6(1):33.
67. Tanchangya T, Rahman J, Siddiqi KO, Islam N, Sarker T, Naher K, Chowdhury S. Factors affecting green banking technology adoption in Bangladesh. Discover Sustain. 2025;6(1):1252.
68. Alshammari SH, Alshammari MH. Factors affecting the adoption and use of ChatGPT in higher education. Int J Inform Communication Technol Educ (IJICTE). 2024;20(1):1–16.
69. Dash G, Paul J. CB-SEM versus PLS-SEM methods for research in social sciences and technology forecasting. Technol Forecast Soc Chang. 2021;173:121092. .
70. Kock N. Common method bias in PLS-SEM: A full collinearity assessment approach. Int J e-Collaboration. 2015;11(4):1–10. https://doi.org/10.4018/ijec.2015100101.
71. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. Eur Bus Rev. 2019a;31(1):2–24. https://doi.org/10.1108/EBR-11-2018-0203.
72. Ho R. Handbook of univariate and multivariate data analysis and interpretation with SPSS. 1st ed. Chapman and Hall/CRC; 2006.
73. Hair JF Jr, Hult GTM, Ringle CM, Sarstedt M. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). 3rd ed. Sage; 2022.
74. Fornell C, Larcker DF. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. J Mark Res. 1981;18(1):39–50. https://doi.org/10.2307/3151312.
75. Hair JF, Ringle CM, Sarstedt M. PLS-SEM: indeed a silver bullet. J Mark Theory Pract. 2011;19(2):139–51. https://doi.org/10.2753/MTP1069-6679190202.
76. Ringle CM, Wende S, Becker J-M. (2022). SmartPLS 4. Oststeinbek: SmartPLS. Retrieved from https://www.smartpls.com/documentation/algorithms-and-techniques/ipma/
77. Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate Data Analysis. 8th ed. Cenage Learning; 2019c.
78. Badr AMM, Al-Abdi BS, Rfeqallah M, Kasim R, Ali FAM. Information quality and students' academic performance: The mediating roles of perceived usefulness, entertainment and social media usage. Smart Learn Environ. 2024;11(1):45. https://doi.org/10.1186/s40561-024-00329-2.
79. Dul J. Identifying single necessary conditions with NCA and fsQCA. J Bus Res. 2016;69(4):1516–23. https://doi.org/10.1016/j.jbusres.2015.10.134.
80. Dul J, Van der Laan E, Kuik R. A statistical significance test for necessary condition analysis. Organizational Res Methods. 2020;23(2):385–95. https://doi.org/10.1177/1094428118795272.
81. Lima TF, Bahli B, Arbulu A, Hamdi A, Saikouk T. Differentiating must–have and should–have supply chain capabilities for enhanced performance: a necessary conditions analysis. J Bus Industrial Mark. 2025;40(2):313–38. https://doi.org/10.1108/JBIM-06-2024-0453.
82. Dul J, Vis B, Goertz G. Necessary Condition Analysis (NCA) does exactly what it should do when applied properly: a reply to a comment on NCA. Sociol Methods Res. 2021;50(2):926–36. https://doi.org/10.1177/0049124118799383.
83. Yu C, Yan J, Cai N. ChatGPT in higher education: Factors influencing ChatGPT user satisfaction and continued use intention. Front Educ. 2024;9. https://doi.org/10.3389/feduc.2024.1354929.
84. Hasan M, Shanto RI, Ishmam HM, Raheeb FR, Shifa AM, Momen S. (2026). Modeling Daily Activity Patterns of Bangladeshi University Students Using Agent-Based Techniques. In R. Silhavy & P. Silhavy, editors, *Software Engineering: Emerging Trends and Practices in System Development* (Vol. 1562, pp. 367–380). Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-04725-0_23
85. Won D, Chiu W, Byun H. Factors influencing consumer use of a sport-branded app: The technology acceptance model integrating app quality and perceived enjoyment. Asia Pac J Mark Logistics. 2023;35(5):1112–33. https://doi.org/10.1108/APJML-09-2021-0709.
86. Talukder NM, Bin Ahsan W. The Impact of AI on Student Engagement in Virtual Learning within Bangladesh's Higher Education Sector. Userhub J. 2025. https://doi.org/10.58947/journal.jtgx34.
87. Pallot M, Pawar K, Krawczyk P, Topolewski M, Lecossier A, Abdel Razek AR. Evaluating User eXperience as a Means to Reveal the Potential Adoption of Innovative Ideas. 2020 IEEE Int Conf Eng Technol Innov (ICE/ITMC). 2020;1–11. https://doi.org/10.1109/ICE/ITMC49519.2020.9198368.
88. Petter S, DeLone W, McLean ER. Measuring information systems success: Models, dimensions, instruments, and measures. J Organizational End User Comput. 2008;20(4):1–28. https://doi.org/10.4018/joeuc.2008100101.
89. Rana MM, Siddiqee MS, Sakib MN, Ahamed MR. Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. Heliyon. 2024;10(18):e37569. https://doi.org/10.1016/j.heliyon.2024.e37569.
90. Kim T, Kim MJ, Promsivapallop P. Investigating the influence of generative AI's credibility and utility on travel consumer behaviour and recommendations through the lens of personal innovativeness. Curr Issues Tourism. 2025;28(14):2220–4. https://doi.org/10.1080/13683500.2024.2364764.
91. Hossain ME, Biswas S. Technology acceptance model for understanding consumer's behavioral intention to use artificial intelligence based online shopping platforms in Bangladesh. SN Bus Econ. 2024;4(12):1–61. https://doi.org/10.1007/s43546-024-00754-y.
92. Emon MMH, Khan T, Rahman MA, Siam SAJ. Factors Influencing the Usage of Artificial Intelligence among Bangladeshi Professionals: Mediating role of Attitude Towards the Technology. 2024 IEEE Int Conf Comput Appl Syst (COMPAS). 2024;1–7. https://doi.org/10.1109/COMPAS60761.2024.10796110.
93. Kim SD. Application and Challenges of the Technology Acceptance Model in Elderly Healthcare: Insights from ChatGPT. Technologies. 2024;12(5):68. https://doi.org/10.3390/technologies12050068.
94. Zou W, Huang Y. To use or not to use? Understanding doctoral students' acceptance of ChatGPT in writing through the technology acceptance model. Front Psychol. 2023;14:1259531. https://doi.org/10.3389/fpsyg.2023.1259531.
95. Miah MS, Singh JSK, Rahman MA. Factors Influencing Technology Adoption in Online Learning among Private University Students in Bangladesh Post COVID-19 Pandemic. Sustainability. 2023;15(4):3543. https://doi.org/10.3390/su15043543.

96. Sallam M. ChatGPT Utility in Healthcare Education, Research, and Practice: Systematic Review on the Promising Perspectives and Valid Concerns. Healthcare. 2023;11(6):887. https://doi.org/10.3390/healthcare11060887.
97. Rahman DH, Rofe RI. AI-powered adaptive learning: a conceptual framework for enhancing higher education in Bangladesh. 2024.
98. Wang M, Yang S. The influence of social influence on consumers' adoption of mobile applications. Int J Mobile Commun. 2012;10(6):556–72. https://doi.org/10.1504/IJMC.2012.049448.
99. Muis KR, Pekrun R. A systematic literature review of user trust in AI-enabled systems: An HCI perspective. Int J Human–Computer Interact. 2022;39(4):693–718. https://doi.org/10.1080/10447318.2022.2138826.
100. Krejcie RV, Morgan DW. Determining sample size for research activities. Educ Psychol Meas. 1970;30(3):607–10. https://doi.org/10.1177/001316447003000308.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.