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RESEARCH ARTICLE

AI Meets Academia: Exploring ChatGPT Use in Higher Education Through the Extended UTAUT Lens

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Abstract: ChatGPT is one of the most popular and rapidly adopted educational technologies. The widespread revolution of ChatGPT and its applications in various spheres of life call for unveiling the factors that stimulate users' behavioral intentions. Thus, this research aims to assess the determinants shaping users' intentions and the actual use of ChatGPT for learning purposes in developing countries. The "Unified Theory of Acceptance and Use of Technology" model with three extended parameters has been adopted for the current study. The extended variables are learning value, information accuracy, and technology anxiety. Data were collected from 619 university students and examined through partial least squares structural equation modeling and artificial neural network techniques. This paper demonstrates that users' ChatGPT use intention is positively influenced by learning value, information accuracy, social influence, facilitating conditions, and performance expectancy. In contrast, technology anxiety has a significant negative association with use intentions, emphasizing that discomfort with technology deters users from using it, which is a prominent observation for artificial intelligence chatbot developers and educators. Use intentions and learning value significantly determine users' actual use behavior. This study further underscores the crucial role of information accuracy, learning value, and technology anxiety in ChatGPT adoption in higher educational settings. The practical implications of this study provide insightful findings for academic stakeholders, developers, administrators, and policymakers of developing countries, particularly concerning the constructive and ethical implementation of ChatGPT in higher education.

Keywords: ChatGPT, learning value, information accuracy, technology anxiety, developing country

1. Introduction

For learning, the use of artificial intelligence (AI) tools redefined the conventional learning space during the era of digital evolution of education, which made the learning experiences more enjoyable. Both customized and collaborative learning have fascinating possibilities that the disruptive power of AI opens [1]. ChatGPT, an AI chatbot, is the most promising of these technological innovations, which has the potential to change the learning system completely [2]. ChatGPT is, nowadays, actively applied in the academic realm to provide additional educational materials, answer learners' questions, and tutor them in different fields [3]. This system allows students to develop their writing competencies by responding to it and getting comprehensive feedback, ideas to improve, and grammar corrections on their writing [4]. Despite the fact that ChatGPT can be used in writing scientific texts, it is important to note that it cannot be considered a comprehensive solution in the process of writing a scientific text. As Montenegro-Rueda et al. [5] note, writers have to apply their

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knowledge, understanding, and critical thinking to validate and complement the information presented by ChatGPT. ChatGPT can also be used in the form of an Exploratorium, where students can find resources to explore and interpret data; a study partner, helping them think critically; and a motivator, where students can get games and challenges to improve learning [6].

However, ChatGPT has also raised ethical concerns in the process of tertiary education. Besides, the increasing number of cheating and plagiarism, ChatGPT has no regulation, which only intensifies the fears of its rapid development without any risk evaluation and standard procedures [2]. However, despite these, it is impossible to deny the adaptive learning opportunities of ChatGPT that can transform the process of learning, allowing it to be even more common, efficient, and optimal among learners of the world [7].

The lack of literature on the usage and adoption of ChatGPT to support the educational process in developing nations is also present since this tool remains in the research preview stage [2]. Hence, there is a need for research in this field to determine the best practices, address potential barriers, and use them to the fullest to enhance the results of the educational process. Conversely, the use of ChatGPT in the learning environment is unlike any other usage of technologies due to the real-time content creation, personalized learning aid, and human-like interactions, which conventional educational technologies (EduTech) do not possess. The implementation of ChatGPT is a key to educational access of developing nations such as Bangladesh because it will help to eliminate educational disparity by offering affordable, reliable, and scalable learning support in a resource-limited setting. In Bangladesh, the teacher-to-student ratio in the public universities has been gradually increasing due to the scarcity of resources in the education sector. The ratio in 1981 was 1:13.4, but in 2020, it had increased to 1:37.5, which creates the problem of insufficient individual attention to the learners on the part of their instructors [8]. As the student-to-teacher ratio increases significantly, learners become increasingly reliant on AI tools to support them and conduct individual learning [9]. Therefore, it is urgent to analyze the factors that make students resort to the use of ChatGPT in their learning. In response to all these gaps, the proposed research is going to explore the characteristics that affect the adoption and use of ChatGPT by scholars at the tertiary level as part of their learning process. The study uses the "Unified Theory of Acceptance and Use of Technology" (UTAUT) model [10] as its core to reveal the forces involved in the adoption of ChatGPT by students in the learning setting. The researchers have chosen the UTAUT model because the results of the model have been confirmed to predict the adoption and use of technologies in various technology areas, such as FinTech [11], mHealth [12], across mobile banking apps [13], intelligent wearable innovation [14], e-commerce [15], and simulated learning platforms [16].

In recent research, it has been pointed out that the value of learning (Sitar-Taut and Mican, 2021) and the accuracy of information [3] play a significant role in stimulating people to use EduTech. Technology in learning also appeals to the students when they are convinced that it can enable them to achieve their learning goals more effectively, save time, and achieve their learning goals effortlessly [17]. When a learning tool is viewed as ineffective or not as useful in enhancing the understanding of learners, it has an adverse impact on their joy and trust in using the tool [18].

Furthermore, the validity of data received through various technologies is vital to the academic development and learning of students because it enables students to arrive at wise decisions and represent credible assumptions [19]. The students are likely to receive and use a learning aid when it provides more precise information [20]. Therefore, learning value (LV) and information accuracy (IA) are part of this study to evaluate the tendencies of students to use ChatGPT in their learning and find out whether they use it.

On the other hand, technology anxiety (TA) is also considered an important predictor of adopting novel EduTech [21]. Many researchers have affirmed the relevance of anxiety in influencing users' reactions to learning novel technologies [22]. Accordingly, this study incorporated the affective construct "technology anxiety" to extend the basic UTAUT model to examine learners' usage intention and effective deployment of ChatGPT in teaching and learning.

Methodologically, this research employs two distinct methods: "partial least squares structural equation modeling (PLS-SEM)," a symmetric approach, and "artificial neural network (ANN)," an asymmetric approach. PLS-SEM allows researchers to investigate the explicit connections among variables [3], while ANN modeling illuminates the complex interactions of variables and the probable causal scenarios that direct us to the expected result [23]. This integrated method provides a strong methodological foundation that offers an extended and nuanced understanding of the factors impacting students' willingness to adopt ChatGPT for educational purposes. Henceforth, this study seeks to enhance the knowledge of ChatGPT adoption by confronting the specific objectives outlined below:

1) To extend the UTAUT model by incorporating LV, IA, and TA to investigate the factors driving students' ChatGPT adoption intention.
2) To integrate SEM and ANN methods to determine the adequate and essential influencing factors of ChatGPT adoption for learning purposes, considering both linear and non linear relationships.

The outcome of this research will enhance the extant literature on information systems (IS) and technology adoption using the UTAUT model within the scope of education. Moreover, the study strives to offer insights to support crafting sustainable strategies and protocols for increasing ChatGPT adoption and enhancing effective user experience in tertiary educational institutions. This research is intended to provide valuable academic, methodological, and operational insights for academic stakeholders, AI chatbot developers, administrators, and practitioners in higher education across developing nations.

2. Related Literature

2.1. ChatGPT insight

ChatGPT has proved to be useful in physics education, where it can complete calculation problems and clarify answers in a very good way [24]. Moreover, ChatGPT has demonstrated academic advising capabilities, giving direct and detailed responses to career-related inquiries. Some scholars point out that ChatGPT can potentially help in promoting learner autonomy, but others warn against the overuse of the tool because of such problems as bias in responses, misinformation, and the issue of academic integrity [25]. This disjunction indicates that ChatGPT has an educational quality that depends not only on its technical accuracy but also on the moral and educational systems. Although the advantages of using ChatGPT have been widely documented, there is little literature that incorporates the technical, ethical, and contextual positions, which leaves a gap in learning how the performance of ChatGPT differs when used in different educational settings.

2.2. ChatGPT among students

According to Mukul and Buyukozkan [26], AI technologies are more accepted in education among young people. At the same time, the study by Helmiatin et al. [27] reported that the vast majority of university students utilize ChatGPT, which implies they are more inclined to adopt it than any other age group.

In technologically developed areas, students appreciate ChatGPT more due to its convenience and cognitive assistance, whereas in developing areas, the issues of authenticity, ethical application, and academic dependency are more profound [28]. These differences can illustrate the influence of social expectations and education systems on the attitude toward AI-assisted education. Despite the findings of previous researchers on the same topic that point to enthusiasm and caution about the use of AI, few of them summarize their results to describe the variation in adoption behaviors based on cultural or regional backgrounds. It is therefore evident that little is known about the impact of contextual variables on the education assimilation of ChatGPT, including social influence (SI), institutional trust, and access equity.

2.3. ChatGPT in Bangladesh

ChatGPT has rapidly gained traction in Bangladesh, with young users being the most active users. According to Tanvir et al. [29], as early as the beginning of 2023, AI-powered educational tools such as ChatGPT are being adopted by the educational establishment and technology corporations. Such organizations are diversifying their products to make them more accessible to the masses. The global health pandemic of COVID-19 increased the use of technological applications such as ChatGPT, which opened up a wide range of possibilities in remote learning. Naher et al. [30] discovered that the adoption of AI systems in education among Bangladeshi students is promoted by perceived benefits, ease of use, and social factors. Another stimulatory factor raised by Rahman et al. [31] is perceived benefits and trust in AI, which influences the desire of students to use this kind of platform. However, the situation in Bangladesh has its peculiarities concerning other areas. The imposition of the system differs, with an institution-driven approach and group incentives being the key to the implementation in Bangladesh, in contrast to the West, where adoption is usually student-driven and self-motivated. Such disparity could be due to the limitations of infrastructure and different degrees of digital preparedness. Furthermore, the issues of data privacy, transparency in algorithms, and regulatory measures are not well-researched in the local literature.

This contradiction demonstrates a major research potential that can be employed to investigate the mediating role of national, cultural, and institutional situations in determining the relationship between user attitudes and technology adoption. The proposed gap will enhance the theoretical knowledge of the role of ChatGPT in developing economies in the context of education.

2.4. Theories, model conceptualization, and hypothesis development

2.4.1. Extended UTAUT model

Information and technology systems research has employed different theories to determine the factors that have a pivotal contribution to the uptake of emerging and innovative technologies. The most popular and representative of such is the "Unified Theory of Acceptance and Use of Technology" (UTAUT), which was created and subsequently advanced by Venkatesh et al. [32] and has been considered the most successful and well-known theory of user uptake and use of technology. The UTAUT model was framed based on eight proven research models: the "Theory of Reasoned Action," the "Technology Acceptance Model (TAM)," the Motivational Model, the "Theory of Planned Behavior (TPB)," the integrated TAM-TPB model, the "Model of PC Utilization or MPCU," and the "Innovation Diffusion Theory". All these frameworks concern various aspects of IS usage behavior.

UTAUT has proven to be a strong explanatory model with a complete ability to explain up to 70% of the behavioral intentions (BIs) to adopt new forms of technology like ChatGPT [32]. With digital transformation, users will need to change their ways of adapting to the new technologies, such as ChatGPT. In an attempt to enhance the UTAUT model, scholars have incorporated additional variables, including perceived risk, perceived trust, and personal innovativeness [33]. Alotaibi [34] has incorporated other variables, like the BI and use behaviors of academics on ChatGPT, into their model to increase the pertinency of the UTAUT model. Besides using four constructs that were used in the original UTAUT model, this study builds on the extended UTAUT by incorporating three contextual variables: LV, IA, and TA. UTAUT model with the addition of these factors, as depicted in Figure 1, gives a holistic approach to studying how the youth will adopt the usage of ChatGPT in the academic context of Bangladesh.

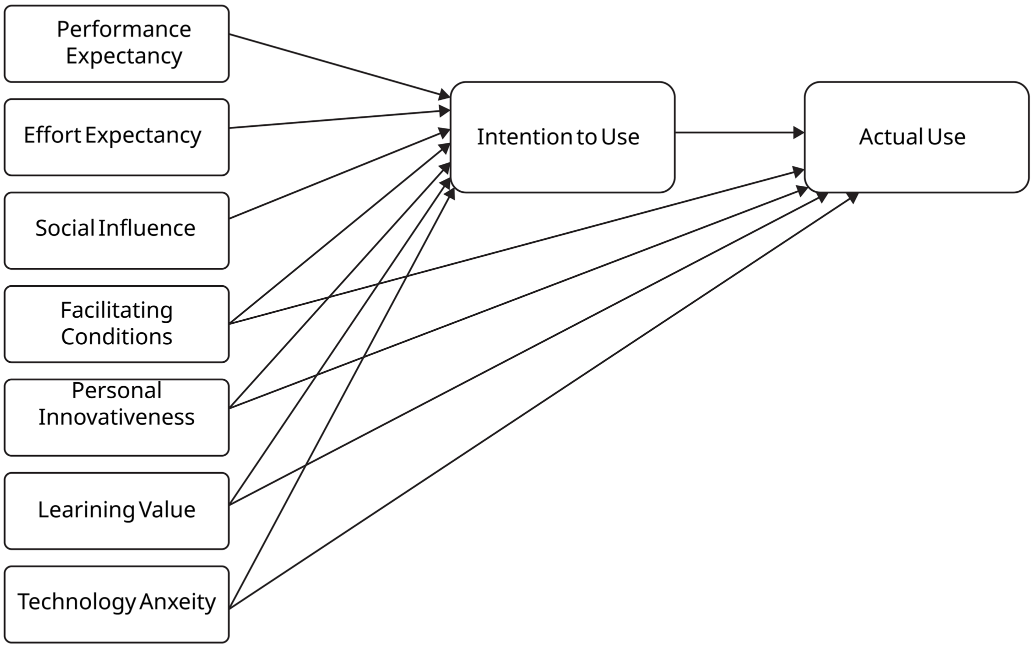
2.4.2. Conceptual framework

This study explores the factors affecting the uptake and utilization of ChatGPT for learning purposes by university students. Although few studies have already investigated the application of various technologies in different contexts, there exists a gap in the literature on discoveries of findings and understanding the major elements that affect AI use in academic settings by the pupils. To address the valuable gaps in the literature, the study uses an extended form of the UTAUT model. The UTAUT model followed in the research makes LV, IA, and TA parallel situational predictors of "performance expectancy (PE) or effort expectancy (EE)" instead of antecedents. Although such constructs may have hypothetical effects on "perceived usefulness and perceived ease of use" [35], the UTAUT concept suggests a wider concept in which the fundamental variables of TAM are incorporated and overridden. LV and IA in the educational context are content-specific cognitive assessments of the perceptions of students about the educational value and informational accuracy of ChatGPT, and TA is the affective component of TA. Previous versions of the UTAUT (e.g., [3, 21]) have been able to handle similar constructs at the identical hierarchical level of PE and EE to explain contextual effects. Accordingly, the use of LV, IA, and TA as parallel determinants is consistent with the flexible nature of UTAUT [32] and adds further explanatory capacity of the framework to domain-specific adoption phenomena. Therefore, the results will provide meaningful information to technology initiators, academic staff, and decision-makers and help to successfully integrate AI tools in tertiary education systems [36].

2.4.3. Hypothesis formulation

Utilizing the proposed conceptual model in Figure 1, this study puts forward several hypotheses to fill the extant research gaps. The next sections will investigate how each aspect of the extended UTAUT model contributes to shaping these hypotheses.

Figure 1
Conceptual framework



1) Performance Expectancy (PE)

PE refers to the belief that using a system will lead to improved performance [32]. It indicates that users are more inclined to use ChatGPT if they acknowledge that it will boost their efficiency [37]. This study assesses how students perceive ChatGPT as an aid that boosts their learning efficiency and outcomes. Research shows PE strongly predicts the adoption of ChatGPT [38]. Therefore, we propose:

H1. PE positively influences students' IU of ChatGPT.

2) Effort Expectancy (EE)

EE refers to the perceived ease of use associated with a technology, or how simple students find ChatGPT to operate. When learners experience minimal difficulty using the system, they are more likely to adopt it [10, 32]. The perceived user-friendliness of technology greatly influences its acceptance. One study indicates that EE is a crucial indicator in forecasting technology uptake [39]. This study will investigate students' views on ChatGPT's ease of use and how it affects their motivation to employ it for learning. Consequently, the subsequent proposition is proposed:

H2. EE positively influences students' IU of ChatGPT.

3) Social Influence (SI)

SI states to the level of notion to which users believe that important personalities in their lives expect them to employ recently developed technologies [32]. SI has a dominant role in the early adoption process, as individuals are very much eager to be aligned with the expectations of their social networks [40]. Studies reveal that SI plays a decisive role in technology adoption, for example, the application of chat interfaces [41]. This study examines how SI affects learners' motives to use ChatGPT for learning. Therefore, we propose:

H3. SI positively influences students' IU of ChatGPT.

4) Facilitating Conditions (FC)

FC involves users' insight into how well technological and structural resources assist in the exploration of a new platform. Venkatesh et al. [10] emphasize that FC is essential for both adopting and effectively deploying information and communication systems. FC is recognized as essential for both the adoption and effective implementation of IS. Prior evidence highlights that supportive infrastructure, training, and accessibility encourage the use of e-learning technologies [42, 43]. Research indicates that adequate FC has a substantial positive impact on learners' motive to use ChatGPT for learning [44]. On the other hand, Sobaih et al. [45] revealed that FC does not have a significant impact on both use intention and actual application and usage of ChatGPT by students in Saudi Arabia. Consequently, based on these insights, the hypotheses proposed for this study are as follows:

H4. FC positively influences students' IU of ChatGPT.

H5. FC positively influences the students' AU of ChatGPT.

5) Learning Value (LV)

In this study, LV highlights ChatGPT's benefits in education, focusing on its perceived utility rather than its cost [46]. LV measures how students view ChatGPT as an instrument for enhancing knowledge, boosting academic achievement, and supporting the learning process. Effective tools like ChatGPT, which provide quick access to materials and support learning objectives, are associated with higher student engagement and confidence [47]. Moreover, empirical findings confirm that LV significantly impacts both the intention and the actual use (AU) of the e-learning context [43]. Thus, based on the discussion and insights, the following assumptions are postulated:

H6. LV positively influences students' IU of ChatGPT.

H7. LV positively influences students' AU of ChatGPT.

6) Information Accuracy (IA)

Drawing from Foroughi et al. [3], IA represents users' perception of the accuracy and reliability of system-generated content. When students consider ChatGPT to be accurate and dependable, their trust and likelihood of usage increase [31]. Therefore, we propose:

H8. IA positively influences students' IU of ChatGPT.

7) Technology anxiety (TA)

Based on Budhathoki et al. [21], TA refers to the unease or apprehension users experience when interacting with new technologies. This anxiety, which includes concerns about complexity and data security, can negatively affect students' technology use intention [48]. Empirical evidence from Budhathoki et al. [21] found that TA has a significantly negative impact on Nepali students' ChatGPT use intention, with an insignificant impact on actual use. Therefore, we propose:

H9. TA negatively influences students' IU of ChatGPT.

H10. TA negatively influences students' AU of ChatGPT.

8) Intention to Use (IU)

IU measures the enjoyment and satisfaction derived from using new platforms, emphasizing fun, playfulness, and entertainment [3]. For ChatGPT, this involves whether students perceive it as enjoyable and engaging in their studies. Influenced by factors like PE and LV, the IU strongly determines how the virtual assistant is ultimately utilized [49]. Consequently, we propose:

H11. IU positively influences students' AU of ChatGPT.

3. Methods

3.1. Measurement items

The proposed framework's latent elements measuring constructs are based on previous research, ensuring their validity and reliability. Appendix A outlines the specific components of each item and their related sources.

3.2. Research paradigm and questionnaire design

In this study, the authors distributed questionnaires to the students of both public and private universities in Bangladesh to collect data from them. A structured questionnaire having two segments was formulated and distributed using Google Forms to obtain key information from participants. The first segment provides a summary of participants, including their gender, age, educational qualifications, and their use of ChatGPT, and the following section includes nine research constructs in the questionnaire. All of the items used in this section are based on a "5-point Likert scale" [50], with 1 being "Strongly Agree" and 5 being "Strongly Disagree." Likert-type data were utilized in this study as they are widely accepted in social behavior assessment and technology or IS adoption research for effectively capturing participants' subjective insights, attitudes, and intentions. The goal of using a "5-point Likert scale" is to elevate quality and response rate while lowering the respondents' levels of discomfort.

3.3. Ethical endorsement of data collection

The institutional review board has approved the ethical issues of the study (Reference Number: NSTU/FBS/EC/2024/4) as it involves data gathering from human subjects. For data collection, all ethical practices were maintained. The data collection team secured informed consent from all the respondents.

3.4. Population, sample size, and sampling strategy

The research targeted university students in Bangladesh, both undergraduate and postgraduate. The literature has confirmed that younger generations are more compatible and have an affinity for emerging technologies [51]. Consequently, students who voluntarily wished to take part in the research were considered. Convenience sampling was employed due to the practical constraints of accessing a diverse population of AI tools users within academic settings and the exploratory nature of the study. This strategy is also consistent with prior UTAUT-based research.

This research employed SEM and ANN for data analysis. For SEM analysis, 200 samples are deemed to be an acceptable sample size, while 300 are considered to be a good sample size [52]. Conversely, Hair et al. [53] suggested that the measuring items used for PLS path association should be taken into consideration while determining the sample size. A sample size that is tenfold the total number of measurement items used is recommended [53]. This study has 33 items. Therefore, a sample size of 330 or higher is applicable for this study.

3.5. Data collection

To gather information from the participants, 720 questionnaires were distributed online. Out of the 720 questionnaires, 657 have been returned by the participants. Among them, 619 questionnaires were correctly filled out, and the remaining ones were deemed invalid. Finally, the study determined a total sample size of 619, which is substantially greater than the rational sample size mentioned in the previous section. The effective response rate was 86%. A six-month time period was applied for data collection, which was from January 17, 2024, to June 25, 2024.

3.6. Statistical assessment of data

For data preprocessing, SPSS 28 has been used, and for measurement and structural modeling, SmartPLS 4.0 has been applied. PLS algorithm determines the qualitative values for measurement and bootstrapping process with 5000 samples and assesses path association to test the hypotheses. For the accuracy of the research constructs, SEM is widely applied to analyze a wide range of phenomena and processes [54]. With a considerable impact on social and economic policymaking, this study measures the stimulators motivating the use of ChatGPT for learning purposes in the context of Bangladesh. Considering the research objectives, the authors adopted SEM for analysis. Moreover, SPSS 28 has been applied for designing ANN models and for determining the "root mean square error (RMSE)" values and normalized importance. ANN was incorporated to complement the PLS-SEM analysis by capturing complex, nonlinear relationships among constructs that traditional linear models may overlook.

Table 1
Demographic details

Factors	Explanation	Frequency	Percentage
Gender	Male	470	75.9%
	Female	149	24.1%
Age	Below 20	11	1.8%
	20–25	563	91.0%
	26–30	37	6.0%
	Above 30	8	1.3%
Education Level	Undergraduate	607	98.1%
	Postgraduate	12	11.9%

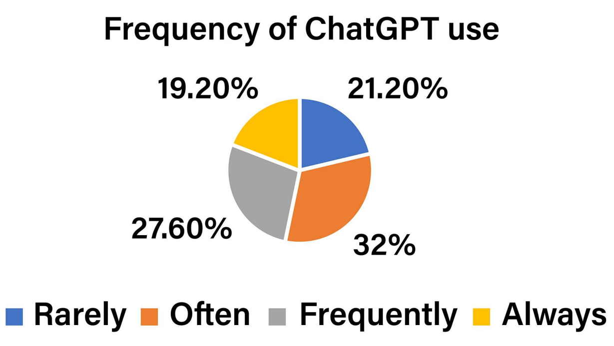
4. Data Analysis

4.1. Demographic statistics

The demographic analysis of survey participants is shown in Table 1. A gender distribution was found in the dataset, which included 619 respondents. 24.1% of participants identified as female (149), while 75.9% of participants identified as male (470). In terms of age distribution, the respondents were split into four groups: 1.8% of respondents were below 20 years, 91% were from 20–25 years, 6% were from 26–30 years, and 1.3% were above 30 years. Regarding educational attainment, 98.1% (607) of respondents were undergraduate students, while 1.9% (12) were graduate students.

Figure 2 depicts the ChatGPT use statistics provided by the study participants of this study. According to this graph, 21.20% use rarely, 32% use often, 27.60% use frequently, and 19.20% always use ChatGPT for educational purposes.

Figure 2
ChatGPT use by students



4.2. Data reliability testing

In this study, “composite reliability (CR),” “average variance extracted (AVE),” and “Cronbach’s alpha” (CA) were investigated in compliance with recognized criteria for assessing the accuracy and reliability of each construct (J. F.) [55]. This reliability test assesses the accurateness and uniformity of the research instruments. Substantial internal consistency is revealed across all constructs by the reliability study. J. F. Hair et al. [55] denote that a CA coefficient greater than 0.70 ensures an internally consistent and dependable methodology for the study. Table 2 illustrates that CA values fall within 0.755–0.927. Therefore, the study has internal consistency.

Convergent validity measures how much the components in a construct converge, as determined by AVE. The AVE values, encompassing 0.574–0.873, are more than the 0.5 threshold requirement (J. F.) [55]. This implies that a substantial percentage of the variance in the constructs is explained by the items that correspond to the constructs. Therefore, it validates the measurement model’s convergent validity.

The robust values of CR, which are above the threshold of 0.7 and range from 0.834 to 0.954, support the internal consistency and reliability of the measurement model (J. F.) [55]. The findings demonstrate the strong validity and reliability of the study’s measurement methods. As a result, the findings support the credibility and dependability of the variables and establish their suitability for evaluating the variables shaping students’ use of ChatGPT for learning.

4.4. Path illustration of structural equation modeling

The causal relationships between a model’s latent constructs are investigated by the structural model [56]. This article examines the SEM for both direct and indirect interactions. Figure 3, constructed using SmartPLS, shows the cross-loadings and *p*-values for analyzing the direct as well as indirect relationships between the constructs.

4.5. Discriminant validity analysis

Discriminant validity estimates how different a construct is from others and confirms that constructs represent different concepts [57]. The “Fornell–Larcker criterion” and the “Heterotrait–Monotrait (HTMT)” ratio were the two techniques used to evaluate discriminant validity [57]. The HTMT ratios for every variable are shown in Table 3. The way to evaluate HTMT discriminant validity is to compare it to a 0.85 threshold [58]. It is recommended that the HTMT value be lower than 0.85. The values in Table 3 are less than the required threshold of 0.85. This advocates that all constructs of the model adequately distinguish from one another and capture distinctive aspects of the study area. The study’s findings show that every construct satisfies this requirement, proving acceptable discriminant validity.

The “Fornell–Larcker criterion” values for constructs are exposed in Table 4. The relationships among the constructs are represented by the off-diagonal components, whilst the diagonal components show the “square root of the AVE” for each construct. By meeting the “Fornell–Larcker criterion,” all diagonal elements show satisfactory discriminant validity, as they are all greater than the comparable off-diagonal elements, as indicated by Fornell and Larcker [59]. All constructs satisfy this requirement,

Table 2
Convergent validity and internal reliability

Constructs	Items	Loadings	CA	CR	AVE
Performance expectancy (PE)	PE1	0.830	0.840	0.893	0.676
	PE2	0.860			
	PE3	0.806			
	PE4	0.791			
Effort Expectancy (EE)	EE1	0.701	0.755	0.843	0.574
	EE2	0.792			
	EE3	0.791			
	EE4	0.743			
Social Influence (SI)	SI1	0.848	0.842	0.894	0.680
	SI2	0.836			
	SI3	0.752			
	SI4	0.858			
Facilitating Condition (FC)	FC1	0.805	0.787	0.862	0.611
	FC2	0.814			
	FC3	0.789			
	FC4	0.714			
Learning Value (LV)	LV1	0.845	0.853	0.901	0.694
	LV2	0.863			
	LV3	0.770			
	LV4	0.851			
Information Accuracy (IA)	IA1	0.920	0.886	0.929	0.814
	IA2	0.914			
	IA3	0.872			
Technology Anxiety (TA)	TA1	0.743	0.812	0.834	0.637
	TA2	0.850			
	TA3	0.944			
Intention to Use (IU)	IU1	0.936	0.927	0.954	0.873
	IU2	0.949			
	IU3	0.918			
Actual Use (AU)	AU1	0.852	0.802	0.883	0.715
	AU2	0.829			
	AU3	0.856			

as seen by the "square root of the AVE's" constant higher values than correlations. Therefore, the model used has strong discriminant validity.

4.6. Multivariate testing statistics

To ascertain the multicollinearity for the study, we examine the "variance inflation factor" (VIF), which ranges from 1.006 to 2.567, remaining below the satisfactory threshold of 5.0 (see Table 5) [60], confirming the nonappearance of multicollinearity issues. Moreover, "common method bias (CMB)" is a vital issue if studies use only one data collection approach. As the VIF values are below 3.3, the study is also free from CMB [61].

4.7. Model fitness

The fitness statistics for the model were assessed using the "Normalized Fit Index" (NFI) and "Standardized Root Mean Square Residual" (SRMR). NFI scores close to 1 show a satisfactory match, while SRMR values less than 0.08 are regarded as acceptable [55]. The findings proved that the model fits well, as the reported result of NFI was 0.914 and SRMR was 0.051, as displayed in Table 5. This boosts confidence in the proposed relationships and affirms the legitimacy of the structural framework.

4.8. Hypothesis testing

Table 6 demonstrates significant parameters such as standard beta, standard error, t-value, and p-value for hypothesis testing. Among 11 hypotheses, 8 hypotheses have been accepted as the p-values for these hypotheses are less than 0.05. PE ($t = 3.642$, $p = 0.000$), SI ($t = 3.066$, $p = 0.002$), FC ($t = 2.044$, $p = 0.041$), LV ($t = 4.624$, $p = 0.000$), IA ($t = 3.484$, $p = 0.000$), and TA ($t = 2.185$, $p = 0.029$) have substantial influence on IU. Similarly, LV ($t = 7.620$, $p = 0.000$) and IU ($t = 8.163$, $p = 0.000$) exhibit a positive influence on AU. Therefore, H1, H3, H4, H6, H7, H8, H9, and H11 have been accepted.

The model incorporates IU as a direct antecedent of AU, consistent with both the TAM and UTAUT frameworks. As shown in Figure 3 and Table 6, IU significantly influences AU

Figure 3
Path diagram with *p*-values and cross-loadings

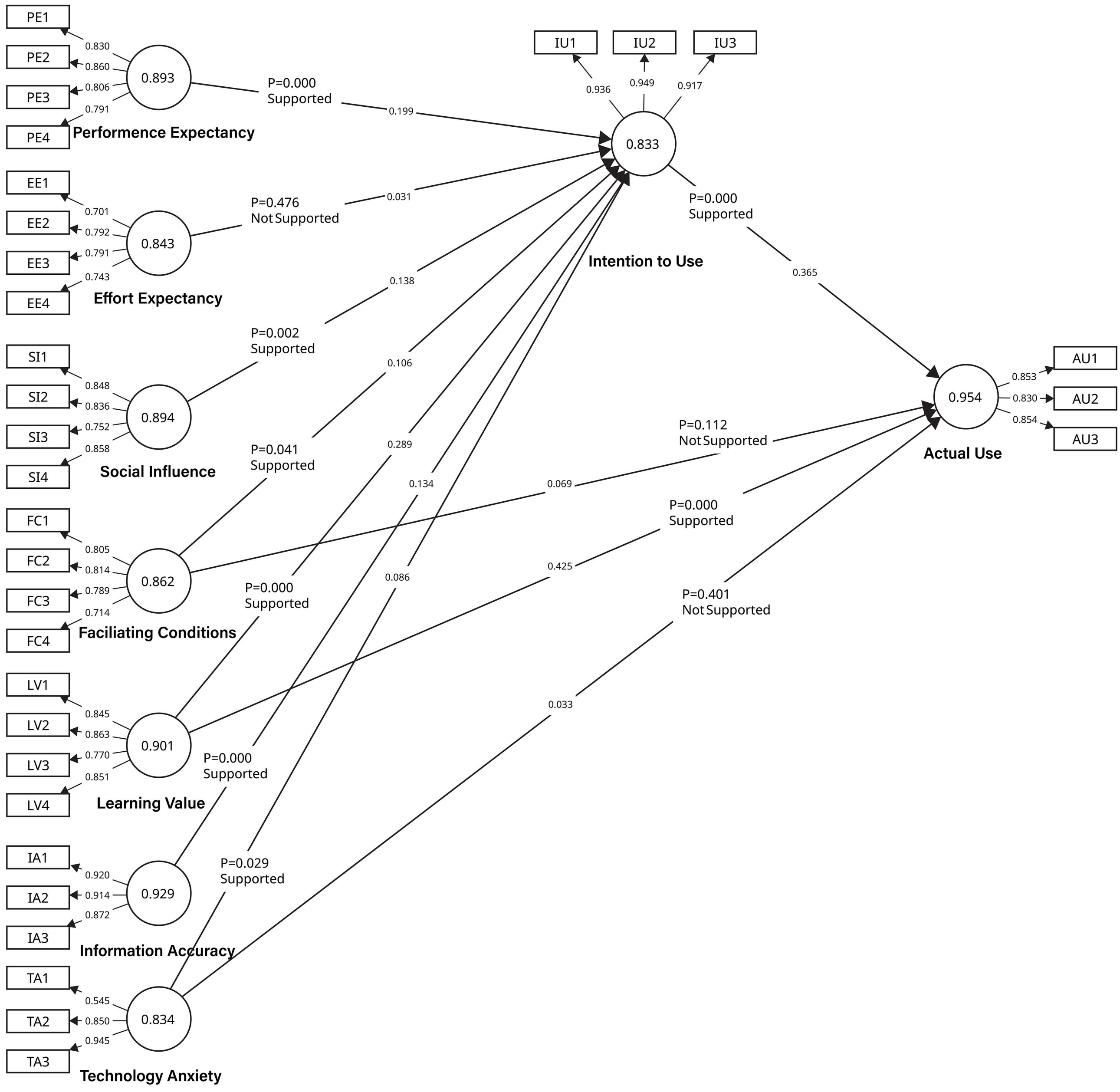


Table 3
HTMT ratios

Constructs	AU	EE	FC	IA	IU	LV	PE	SI
EE	0.784							
FC	0.720	0.836						
IA	0.641	0.594	0.583					
IU	0.795	0.661	0.684	0.548				
LV	0.862	0.812	0.838	0.636	0.749			
PE	0.789	0.848	0.772	0.527	0.708	0.816		
SI	0.633	0.615	0.662	0.566	0.606	0.673	0.682	
TA	0.448	0.426	0.405	0.386	0.323	0.363	0.329	0.388

Table 4
Fornell–Larcker criterion

Constructs	AU	EE	FC	IA	IU	LV	PE	SI	TA
AU	0.846								
EE	0.628	0.757							
FC	0.577	0.651	0.846						
IA	0.543	0.490	0.490	0.902					
IU	0.691	0.565	0.586	0.498	0.934				
LV	0.719	0.666	0.687	0.553	0.671	0.833			
PE	0.653	0.691	0.631	0.454	0.628	0.694	0.822		
SI	0.523	0.503	0.541	0.490	0.538	0.573	0.576	0.824	
TA	0.252	–0.302	0.256	0.243	–0.204	0.338	0.306	0.228	0.798

Table 5
Model fitness data

Fitness statistics	Saturated model
SRMR	0.051
d_ULS	1.372
d_G	0.585
Chi-square	2653.602
NFI	0.914

Note: SRMR = "Standardized Root Mean Square Residual," d_ULS = "Unweighted Least Squares Discrepancy," d_G = "Geodesic Discrepancy," NFI = "Normalized Fit Index."

(β = 0.365, $p < 0.001$), validating the causal pathway. This finding confirms that students' BI strongly predicts their actual use of ChatGPT for learning, thereby reinforcing the theoretical robustness of the proposed model.

However, EE ($t = 0.714$, $p = 0.476$) does not have any positive impact on IU. Likewise, FC ($t = 1.590$, $p = 0.112$) and TA ($t = 0.839$, $p = 0.401$) do not have a noteworthy impact on AU. Hence, H2, H5, and H10 have been rejected.

f^2 implies the extent to which exogenous variables impact the R-squared values of endogenous variables. The effect size can be small, medium, and large if f^2 values exceed 0.02, 015, and 0.35, respectively [62]. This study exhibits several influences ranging from insignificant to significant, as shown in Table 6.

4.9. Current and future usage of ChatGPT

Table 7 and Figure 4 show the current and future levels of ChatGPT use for educational purposes by students. 55% of students currently use ChatGPT, and 54% of students plan to use this tool in the future for their educational purposes.

4.10. Analysis of artificial neural network (ANN) results

ANN simulates the human brain, and it significantly learns from the previous data. Neural networks can perceive the complex nonlinear associations between the variables and technology adoption decisions [63]. Significant predictors from the SEM investigation are considered as input to design the neural networks, and the relative importance of each predictor is also measured using SPSS 28. SEM analysis tests hypotheses, which ANN can't serve, and ANN ranked predictors with precise accuracy, which SEM can't do [64]. Therefore, ANN models are applied along with SEM analysis to complement results in technology adoption research.

ANN models have three layers: input, hidden, and output layers. Input layers represent significant independent variables,

Table 6
Direct connections

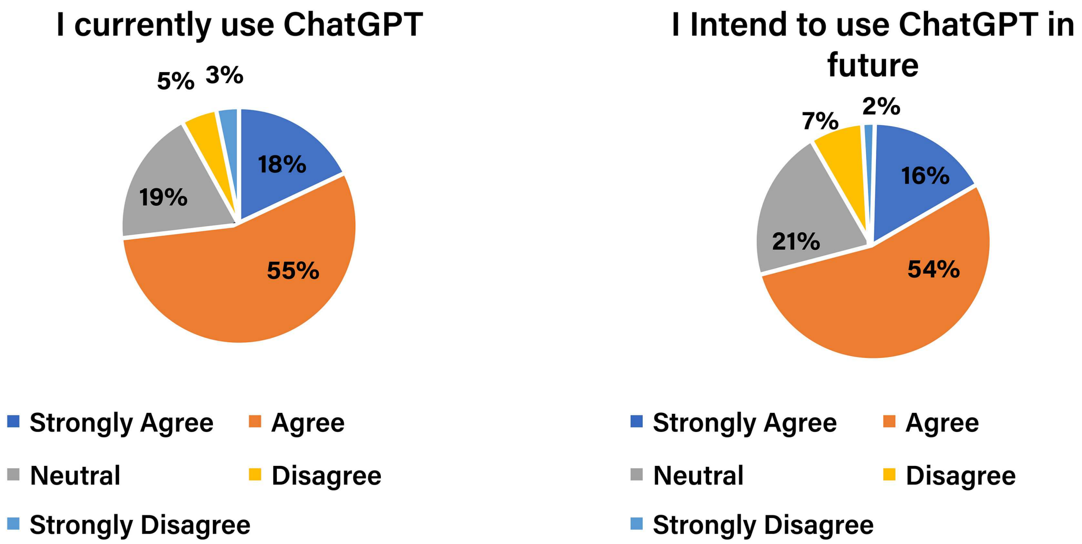
H	Relations	Std beta	Std error	t values	p-values*	f^2	VIF	Decision
1	PE -> IU	0.199	0.055	3.642	0.000	0.194	2.567	Supported
2	EE -> IU	0.031	0.043	0.714	0.476	0.009	2.421	Not supported
3	SI -> IU	0.138	0.045	3.066	0.002	0.027	1.865	Supported
4	FC ->IU	0.106	0.052	2.044	0.041	0.021	2.306	Supported
5	FC -> AU	0.069	0.043	1.590	0.112	0.006	2.006	Not supported
6	LV-> IU	0.289	0.062	4.624	0.000	0.266	2.768	Supported
7	LV -> AU	0.426	0.056	7.620	0.000	0.390	2.567	Supported
8	IA -> IU	0.134	0.038	3.484	0.000	0.028	1.680	Supported
9	TA -> IU	–0.086	0.039	2.185	0.029	0.022	1.149	Supported
10	TA -> AU	0.033	0.039	0.839	0.401	0.003	1.006	Not supported
11	IU -> AU	0.365	0.045	8.163	0.000	0.383	1.926	Supported

* at the significance level of < 0.05.

Table 7
Current and future usage of ChatGPT

	I currently use ChatGPT		I intend to use ChatGPT in the future	
	Frequency	Percentage	Frequency	Percentage
Strongly agree	114	18	102	16
Agree	343	55	338	54
Neutral	116	19	127	21
Disagree	31	5	42	7
Strongly disagree	15	3	10	2

Figure 4
Current and future usage of ChatGPT



and the output layer shows the dependent variable. The hidden layer works like a black box by applying the knowledge stored in nodes, which is also known as synaptic weights [65]. Synaptic weights, which are modified by an interactive process of learning, are the connection strengths of the neurons or nodes in all layers of ANN [23]. Among four groups of neural network models, the multilayer perceptron model has been used for this study [66].

To deal with the overfitting problem, a 10-fold cross-validation process has been adopted [67]. Total data have been separated into two groups: 70% for training and 30% for testing [66]. Although there is no agreed-upon decision on the number of hidden neurons, Alam et al. [68] recommend using a node within the range of 1–10 hidden nodes. For model A, significant predictors FC, IA, LV, PE, SI, and TA are the inputs, and IU acts as the output, as shown in Figure 5. For model B, there are only two input factors (IU and LV) and one output factor (AU) as demonstrated in Figure 6.

Table 8 shows the RMSE values for both models along with the mean and standard deviation (SD). In model A, the mean RMSE is 0.466 and 0.497 for training and testing, respectively, and the SD is 0.062 and 0.032 for training and testing, respectively. In model B, the mean RMSE is 0.451 for training and 0.464 for testing, and the SD is 0.014 for training and 0.023 for testing. A very low SD with a relatively small mean RMSE indicates significant predictive accuracy of the results. Therefore, the analysis reveals a strong predictive accuracy of the models with small values for both mean and SD of RMSE.

Table 9 provides the sensitivity analysis of neural networks for both models. Normalized importance is determined by dividing the average importance of each factor by the highest importance. The findings inferred that LV is the strongest predictor of the use intention of ChatGPT, followed by PE, FC, SI, IA, and TA. On the other hand, for actual use behavior (AU), IU is the strongest predictor, followed by LV.

5. Discussion

The research intends to examine the effect of the extended UTAUT model's factors on BI to use ChatGPT by tertiary students. The UTAUT model has been extended with LV, IA, and TA as these variables are relevant to the educational context. Therefore, this study has proposed eleven hypotheses, which have been tested using PLS-SEM. Then, ANN models were formulated, and normalized importance was presented with significant factors from PLS-SEM to reflect the nonlinear relationship between predictors and dependent variables.

The findings show that PE and IU have a positive correlation, which corresponds to the research of Al-Emran et al. [69] and Foroughi et al. [3]. The positive relation happens as learners frequently use ChatGPT to get customized as well as relevant information in a faster and easier way for various areas of learning. ChatGPT reduces the challenges they face in gathering information, generating creative ideas, interpreting ideas, and so on. Furthermore, this tool has dynamic use for education through

Figure 5
Model A

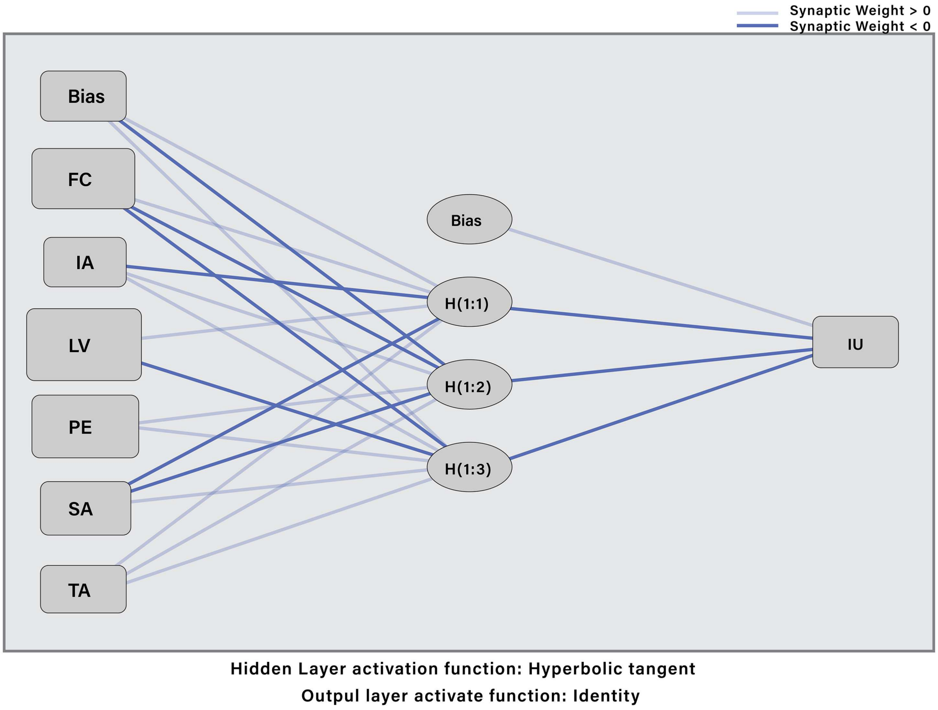


Figure 6
Model B

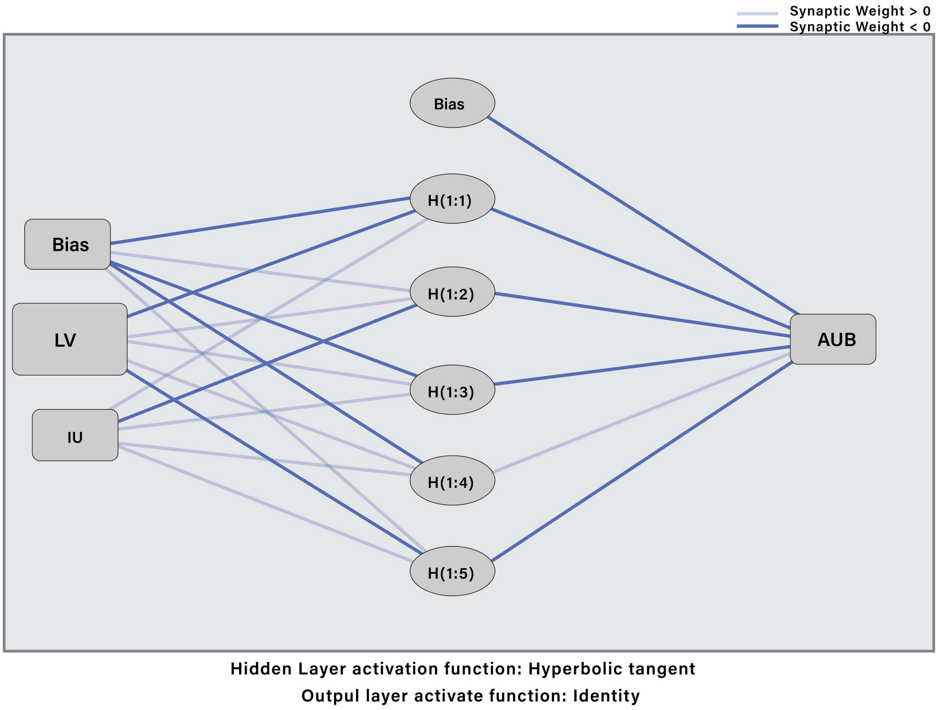


Table 8
RMSE of Model A and Model B

	Model A		Model B	
Network	RMSE (Training) (Input: FC, IA, LV, PE, SI, TA) (Output: IU)	RMSE (Testing) (Input: FC, IA, LV, PE, SI, TA) (Output: IU)	RMSE (Training) (Input: IU, LV) (Output: AUB)	RMSE (Testing) (Input: IU, LV) (Output: AUB)
1	0.479	0.482	0.477	0.488
2	0.504	0.502	0.469	0.466
3	0.500	0.508	0.448	0.411
4	0.499	0.504	0.451	0.442
5	0.491	0.498	0.433	0.454
6	0.483	0.475	0.432	0.475
7	0.478	0.464	0.446	0.480
8	0.476	0.570	0.447	0.480
9	0.462	0.516	0.460	0.474
10	0.293	0.455	0.443	0.469
Mean	0.466	0.497	0.451	0.464
SD	0.062	0.032	0.014	0.023

Table 9
Sensitivity analysis

	Model A			Model B	
	Average importance	Normalized importance		Average importance	Normalized importance
FC	0.16	58%	LV	0.577	100%
IA	0.12	39%	IU	0.423	74%
LV	0.28	100%			
PE	0.20	73%			
SI	0.15	54%			
TA	0.10	38%			

which learners accomplish their learning objectives. Therefore, students are interested in using ChatGPT for education.

However, the insignificance of EE in predicting IU diverges from several technology adoption studies [69] but can be rationalized in the context of ChatGPT. The causes of divergence can be many. First, ease of use or effort to apply new technology is a vital indicator, but within a short time, ChatGPT received significant popularity among users. Moreover, Østergaard [70] found that ChatGPT users increased by 1 million within 5 days, which reveals the widespread usage of ChatGPT. Hence, ChatGPT is not new to tertiary students, for whom effort may not be a significant influencer in adopting ChatGPT. Second, tech-savvy people such as university students may ignore perceived effort as they are sound enough on technology use. Likewise, as an AI tool characterized by intuitive usability and conversational simplicity, ChatGPT presents minimal cognitive load. Consequently, students perceive negligible effort in its operation, which compresses the response variance, a ceiling effect, and diminishes EE's statistical impact. Furthermore, phrasing of EE items (e.g., "the degree of effort to use ChatGPT") may have been interpreted inversely by respondents, where low perceived effort indicated ease of use but did not translate into higher intention scores. This aligns with the observation that when technology is universally easy to use, EE becomes a hygiene factor rather than a motivator.

The result manifests that SI is positively related to ChatGPT use in the education context, which corroborates the conclusions drawn by the study in literature [69] and contradicts the outcomes of Foroughi et al. [3]. Even though the association between SI and IU is positive, SI has a small impact on IU, as explained by the effect size and normalized importance. The reason is that social pressure usually works better for public tools like social networking media. As ChatGPT use remains private and users' unique requirements drive them to use ChatGPT, peer influence is insignificant for ChatGPT use by students.

One of the novel discoveries of this study is that FC has a positive relation with IU but no relation with AU, which is completely different from the study by Strzelecki [71]. This happens because having a favorable environment might encourage the use intention, but actual use completely depends on users' specific needs. Other barriers that contribute to translating student use intention to actual use can be time constraints and the availability of substitute tools. Moreover, regardless of FC, other external factors might have a significant role in this transition from intention to actual use, for example, students' intrinsic motivation.

LV, a new and extended variable, has a noteworthy and positive influence on both IU and AU, which aligns with the findings of Foroughi et al. [3]. Surprisingly, LV is the strongest predictor of IU, which is unique to the context of ChatGPT use in teaching and learning, particularly in Bangladesh as instructors couldn't provide special care to the specific learning needs of each student due to large class size and high teacher-to-student ratio [8]. University students intend to use ChatGPT, considering the perceived LV of this tool. ChatGPT, an interactive and self-paced learning aid, facilitates learners in understanding difficult lessons, substituting traditional study resources, getting constructive feedback, and accomplishing academic tasks. LV, as a result, is the fundamental determinant of ChatGPT adoption by pupils in Bangladesh. There is a very limited study on LV's impact on ChatGPT adoption. Therefore, it is recommended to be a mediating factor stimulating the association between other factors and BI in future research.

The observed connection between IA and IU is found to be positive, which is a novel finding of this study. ChatGPT provides accurate information, which enhances trust and satisfaction among users. IA also reinforces positive experiences and contributes to this positive association. Moreover, this factor can further be studied as a mediator or moderator between other variables and IU ChatGPT.

TA has negative consequences on the IU of ChatGPT adoption. Contrarily, the negative association between TA and AU is found to be insignificant. Both findings are in line with Budhathoki et al. [21]. Although students initially may have reluctance to use ChatGPT, academic deadline pressures, and encouragement to use effective learning tools lead to actual use. Besides, support and experience from other users, a supportive environment, and academic requirements mitigate the anxiety, resulting in actual use. Finally, IU has a favorable impact on AU as predicted.

SEM findings alone cannot represent the intricate relationship between variables; ANN analysis has been conducted. Moreover, the outcomes of PLS-SEM do not provide the importance of the predictors. Therefore, to measure the precedence of predictors, ANN models and sensitivity analysis have been assessed. This research found six factors out of seven that predict the ChatGPT use intention. The ANN analysis shows that LV is the strongest indicator of ChatGPT use intention of Bangladeshi students, followed by PE, FC, SI, IA, and TA. Similarly, IU is the strongest predictor for AU, followed by LV. Moreover, the current and future use by university students has been investigated. It has been observed that 55% of learners currently use ChatGPT, and the rest who are not using it currently will use it in the future. Therefore, ChatGPT has a great prospect among tertiary students in Bangladesh.

While the current study also exhibits the potential of ChatGPT to enhance efficiency and support students' academic writing, it is essential to acknowledge the accompanying ethical implications. The use of AI-generated content in academic activity poses some questions in terms of originality, transparency, and privacy of data. Students of higher education need to make sure that they implement ChatGPT as an aid tool, not a replacement for critical thinking and research. The engagement of AI should be properly disclosed as prescribed by the principles of academic integrity, which is supposed to be a normal practice to ensure transparency.

6. Implications, Limitations, and Future Research Avenues

6.1. Theoretical implications

This work has added value to the current theoretical debate on the extension of UTAUT due to the presentation that domain-specific constructs like LV and IA can play direct roles as IU and do not necessarily serve as antecedents of PE or EE. This intervention maintains the theoretical consistency of UTAUT and the incorporation of greater contextual validity in EduTech, specifically AI-based learning systems.

Besides, the present study makes vital contributions to the literature discussing the IU ChatGPT among tertiary students of Bangladesh. This research offers a series of contributions to the UTAUT model by including contextual conditions: LV, IA, and TA to determine the BIs of users to use ChatGPT in education in Bangladesh.

This research will indicate the interactions of contextual and psychological variables with BIs to influence the real use to increase the exploratory competence and relevance of the UTAUT model within the EduTech context. Our study results validated the direct effect of LV and accuracy of the information on the students adopting ChatGPT as a tool to learn. The association of TA and IU was also found to be negative, as shown in the results. On the contrary, the negative interdependence between TA and AU turned out to be not significant. Thus, the results (H7, H8, H9, H10, and H11) will give new possibilities to prospective researchers. Such findings of the study may be applied to explore the inclinations, the needs, the level of concrete use of EduTech, and human–AI relationships in education in the target audiences.

6.2. Practical implications

Together with the academic staff, the study has practical implications for the stakeholders involved in the provision of services through chatbots by disclosing the main driving forces of use intention and actual use of ChatGPT. Since PE is a critical indicator that triggers ChatGPT usage, it is essential to increase the usefulness of the system for students. In this regard, the students are expected to receive clear facts regarding the positive sides of using ChatGPT, such as faster responses and more accurate answers. Educators and learning institutions can support students to use ChatGPT in their studies by providing resources, such as user guidelines, tutorials, and help centers.

The results of our research also reflect that there is a positive correlation between SI and ChatGPT use in education, which promotes the extent of their promotion to increase the awareness of users on this EduTech. SI can be improved by convincing early adopters to tell their stories, which are positive.

Furthermore, the LV, the accuracy of information, and TA are included in the UTAUT model in this study, bringing some valuable results. The results of our research proved that the LV is an incentive that learners need to get educated by ChatGPT. The community of ChatGPT design and development should aim at enhancing the educational value of the platform to allow it to meet the expectations of learners. This could include the incorporation of other learning aspects or the provision of specialized learning routes that are reliant on the individual needs of every student. The educators ought to endeavor to create a culture of innovation that can encourage the students to test new educational applications and learning tools that have been recently invented. The developers of ChatGPT ought to consider incorporating the platform with other technologies and tools that are commonly taught in a classroom.

The positive correlation between IA and IU, also identified in this paper within the framework of ChatGPT, is a new development. Measurement of IA will strengthen positive experiences and hasten the willingness of learners to use and learn ChatGPT for their educational purposes. Users tend to be more accepting of the technology if they feel that the technology provides them with reliable and accurate information. Offering training to the students to understand how to check the information provided by ChatGPT and create policies on how to assess information produced by AI critically will enhance the level of IA, which will serve as an invisible hand to boost the rate of use of ChatGPT.

The factor that is also worth mentioning in terms of contribution to this research is the usage of TA as a contextual variable added to the extended UTAUT model. In this study, there was a negative impact of TA on IU. Conversely, no evidence of a negative relationship between TA and AU appears, and this is a revelation in this study. TA can be minimized with the help of appropriate training and assistance, and this can help in adopting new mid-tech, which is ChatGPT. To ensure that the impacts of ChatGPT on student learning are optimized, concerned authorities need to periodically assess this effect and reach a data-driven conclusion that will enhance its use and integration.

The study is context-specific in offering higher education guidance in Bangladesh. In light of the ongoing digitalization of the country and the lack of even institutional preparedness, there is an urgent need to enhance digital literacy among educators and learners by providing them with professional development opportunities. Institutions must embrace incremental AI implementation in line with institutional capacity to make AI sustainable in the education sector. To integrate AI in the academic sector in a sustainable manner, universities, the University Grants Commission, the Ministry of Education, and technological partners need to collaborate.

6.3. Limitations and future directions

This study has several research shortcomings that open the doors to the possibilities of further research. First, the authors concentrated on the students of Bangladeshi universities. It is possible that different results would be obtained if the study involved the students of other levels of education in Bangladesh or other developing nations.

Second, in spite of the fact that this study satisfies the minimum sample size criteria, as suggested by Hair et al. [53], future studies will be able to collect more data to enhance the accuracy of the ChatGPT adoption paradigm in the learning environment. Further research can be used in the future to diversify the sample with diversified institutions in various geographical and social backgrounds to enable such comparative research works.

Third, the moderating issue(s) of demographic variables: age group, gender, willingness, and experience have been ignored in this study, which future studies may incorporate. Future research can rediscover other important findings by looking at the buffering actions of various environmental and contextual specifics, such as individual innovativeness, technological experience, task-technology fit, and government programs.

Furthermore, convenience sampling and self-reported Likert-type data were utilized in this study, which could limit the generalizability of the results and develop a possible bias in response. Nevertheless, this strategy is not new regarding the previous UTAUT-related studies examining the novel technologies within the learning environment. Therefore, this study needs to be extended through additional researches that use more representative sampling designs. In the future, researchers can do longitudinal research to identify and compare the alterations of these stimulating variables with the experience.

7. Conclusion

ChatGPT has become a cutting-edge and dynamic tool for educators aiming to enhance student-teacher interactions while strengthening the pedagogical experience (Firat, 2023). Despite that, the deployment of this AI chatbot in many developing countries has yet to reach the expected level (Kshetri, 2023). To bridge this gap, our study focused on identifying the determinants influencing users' intentions to adopt ChatGPT for educational purposes in the scenario of a developing nation, Bangladesh. Our paper employs the UTAUT model as its foundational basis to uncover the determinants impacting students' adoption of ChatGPT in education. To reveal insights from several perspectives, the authors expanded the original UTAUT model by adding three context-specific determinants: LV, IA, and TA. The authors blended two different methods—PLS-SEM, a symmetric approach, and ANN, an asymmetric approach—to analyze data gathered from 619 respondents. PLS findings show that PE and SI positively impact IU. Another novel finding of this study is that the FC has a positive relation with IU but no relation with AU. Surprisingly, this research uncovered that EE is not a significant predictor of ChatGPT adoption by students. Another noteworthy discovery of this research is that LV and IA positively affect both IU and AU. TA, an extended variable in the ChatGPT adoption model, negatively impacts IU. However, the inverse relationship between TA and AU is found to be insignificant, which is a key finding of this study. ANN analysis is employed to measure the precedence of predictors, which shows that LV is the leading determinant of ChatGPT use intention of Bangladeshi students, followed by PE, FC, SI, IA, and TA. IU is the strongest predictor for AU, followed by LV. The applications of EduTech products are anticipated to expand substantially in the coming years. AI chatbot facilitators and policymakers should prioritize optimizing the forces that affect users' BI and AU of this service for educational purposes.

Ethical Statement

All subjects provided informed consent for inclusion before participating in the study. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the institutional review board of the Dean's Office, Faculty of Business Studies, Noakhali Science and Technology University (NSTU), Bangladesh (Reference No.: NSTU/FBS/EC/2024/4).

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Afruza Haque: Conceptualization, Methodology, Formal analysis, Resources, Data curation, Writing – original draft, Writing – review & editing, Supervision, Visualization. **Rasheda Akter Rupa:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Rana Al Mosharrafa:** Resources, Validation, Investigation, Data curation, Writing – original draft, Visualization. **Shaharin Akter:** Software, Validation, Resources, Data curation, Writing – original draft. **Abu Naser Mohammad Saif:** Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Rehnuma Mostafa:** Validation, Resources, Writing – review & editing.

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Appendix A

Measurement constructs

Variable (symbol)	Indicator	Measuring instrument	References
Performance expectancy (PE)	PE1	Using ChatGPT would assist me in completing learning tasks faster.	Venkatesh et al. [10]; Foroughi et al. [3]
	PE2	ChatGPT would help me increase my learning performance.	
	PE3	ChatGPT would help me be more productive while learning.	
	PE4	ChatGPT could make learning easier.	
Effort expectancy (EE)	EE1	Learning how to use ChatGPT is easy for me.	Venkatesh et al. [10]; Foroughi et al. [3]
	EE2	I clearly understand my interaction with ChatGPT.	
	EE3	ChatGPT makes learning simple for me.	
	EE4	Being skilled at using ChatGPT is easy for me.	
Social influence (SI)	SI1	People who are important to me believe I should use ChatGPT in my education.	Venkatesh et al. [10]; Foroughi et al. [3]
	SI2	People who influence my behavior think I should use ChatGPT for my studies.	
	SI3	I'm more likely to use ChatGPT for educational purposes if my friends use it.	
	SI4	People whose opinions I value prefer my use of ChatGPT for my studies.	
Facilitating condition (FC)	FC1	I have the knowledge essential to use ChatGPT in my studies.	Venkatesh et al. [10]; Foroughi et al. [3]
	FC2	I have the resources required to use ChatGPT for my study.	
	FC3	ChatGPT is compatible with other ICT tools I use in my studies.	
	FC4	When I experience any complication in learning how to use ChatGPT, I can find help from others.	
Learning value (LV)	LV1	Using ChatGPT broadens my knowledge and contributes to my academic achievement.	Foroughi et al. [3]; AI-Rahim and Zeki (2017)
	LV2	ChatGPT is an effective teaching instrument and helps me to progress my learning process.	
	LV3	ChatGPT helps me find materials faster.	
	LV4	ChatGPT assists me in attaining my learning objectives.	
Information accuracy (IA)	IA1	The information I obtained from ChatGPT is correct.	Filieri and Mcleay (2024); Foroughi et al. [3]
	IA2	The information I obtained from ChatGPT is accurate.	
	IA3	The information I obtained from ChatGPT is reliable.	
Technology anxiety (TA)	TA1	I feel anxious about using ChatGPT	Budhathoki et al. [21]; Sussman and Siegal (2003)
	TA2	I feel anxious about losing my personal information if I do anything wrong while using ChatGPT.	
	TA3	I hesitate to use ChatGPT because of making mistakes that I can't correct.	

(*Continued*)

(*Continued*)

Variable (symbol)	Indicator	Measuring instrument	References
Intention to use (IU)	IU1	I intend to use ChatGPT for my study purposes in the future.	Venkatesh et al. [10]; Foroughi et al. [3]
	IU2	I plan to use ChatGPT for my study purposes in the future.	
	IU3	I predict that in the future, I will use ChatGPT for my study purposes.	
Actual use	AU1	Using ChatGPT is a pleasant experience.	Venkatesh et al. [10]; Foroughi et al. [3]
	AU2	I am currently using ChatGPT for my studies.	
	AU3	Use of ChatGPT for learning is a good idea.	