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Acceptance of ChatGPT by undergraduates in Sri Lanka: a hybrid approach of SEM-ANN

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Abstract

Purpose – This study aims to investigate Sri Lankan Government university students' acceptance of Chat Generative Pretrained Transformer (ChatGPT) for educational purposes. Using the unified theory of acceptance and use of technology 2 (UTAUT2) model as the primary theoretical lens, this study incorporated personal innovativeness as both a dependent and moderating variable to understand students' ChatGPT use behaviour.

Design/methodology/approach – This quantitative study used a questionnaire survey to collect data. A total of 500 legitimate undergraduates from 17 government universities in Sri Lanka were selected for this study. Items for the variables were adopted from previously validated instruments. Partial least squares structural equation modelling (PLS-SEM) using SmartPLS 4 was used to investigate latent constructs' relationships. Furthermore, the variables' relative relevance was ranked using a two-stage artificial neural network analysis with the SPSS 27 application.

Findings – The results of the analysis revealed that eight of the nine proposed hypotheses were confirmed. The most significant determinants of behavioural intention were habit and performance expectancy, closely followed by hedonic motivation and perceived ease of use. Use behaviour was highly influenced by both behavioural intention and personal inventiveness. Though personal innovativeness (PI) was suggested as a moderator, the relationship was not significant.

Research limitations/implications – The research highlights the impact of habit, performance expectancy and perceived ease of use on students' acceptance of AI applications such as ChatGPT, emphasising the need for efficient implementation techniques, individual variations in technology adoption and continuous support and training to improve students' proficiency.

Originality/value – This study enhances the comprehension of how undergraduate students adopt ChatGPT in an educational setting. The study emphasises the significance of certain variables in the

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UTAUT2 model and the importance of PI in influencing the adoption of ChatGPT in educational environments.

Keywords ChatGPT, Personal innovativeness, UTAUT, Artificial neural network, Artificial intelligence, Sri Lanka

Paper type Research paper

1. Introduction

Artificial intelligence (AI) refers to the science and technology field that focuses on producing systems capable of performing tasks usually associated with intelligent beings, such as learning, judgement and decision-making (Axcell and Ellis, 2023). The efficacy of AI has been demonstrated in tackling complex challenges across diverse fields, including education (Devisakti and Muftahu, 2022). Using AI within natural language processing (NLP), sophisticated chatbots and virtual assistants to comprehend and generate human language have been developed (Pillai *et al.*, 2023). ChatGPT is an exceptionally powerful chatbot that uses AI technology. This AI tool was released to the general public on November 30, 2022. Its popularity was evident, as it amassed a huge subscriber-base within the first week of its launch. According to Rospigliosi (2023), ChatGPT is a product of the OpenAI language model and has undergone training on an extensive amount of human dialogues. This has enabled it to execute intricate operations and generate responses that closely resemble those of humans. According to Al-Emran *et al.* (2020), ChatGPT uses advanced deep-learning methodologies to comprehend, manipulate and produce natural human language that exhibits a considerable degree of sophistication while ensuring satisfactory precision and practicality.

The implementation of ChatGPT has sparked discussions regarding the potential benefits and drawbacks of AI technologies, as well as their implications for education. In spite of its versatile applications across different domains, the introduction of ChatGPT into the educational sphere has prompted debates on its potential impact (Al-Azawei and Alowayr, 2020; Alshurideh *et al.*, 2023). The emergence of generative AI, as exemplified by ChatGPT, has raised concerns regarding its potential impact on diverse industries and institutions. Higher education can make use of the ChatGPT platform, which presents an opportunity to rethink the role of teaching and learning as well as its potential to enhance the learning process (Malik *et al.*, 2021; Strzelecki, 2023). Instead of exclusively relying on software-based evaluation, educational institutions may opt to use ChatGPT to impart knowledge about critical reasoning and composition and highlight the significance of AI in contemporary society. ChatGPT is thought to be a useful tool for inclusive, creative teaching and assessment that corresponds to a transforming relationship with knowledge. The potential applications of ChatGPT in higher education can be examined through various domains, such as the creation of academic tasks (Tewari *et al.*, 2023), the generation of fraudulent citations (Shoufan, 2023), the encouragement of careful consideration in the application of AI in society (Rospigliosi, 2023) and the facilitation of essay composition (Yoon *et al.*, 2015). Academic institutions are considering the consequences of AI chatbots, and some educators have already incorporated them into their teaching to emphasise their limitations and evaluate their effectiveness. Educational institutions are evaluating the potential implications of ChatGPT for pedagogy and knowledge acquisition in higher education. The broad and transformative possibilities of this technology have thus prompted scholarly interest (Farrokhnia *et al.*, 2023).

Several emerging themes can be discerned through an examination of peer-reviewed literature pertaining to the utilisation of ChatGPT in the context of higher education and academia. The utilisation of ChatGPT has mainly been observed in general education, as reported by Devisakti and Muftahu (2022). However, current discourse predominantly centres on its application in medical education Choudhury and Shamszare, (2023). Foroughi *et al.* (2023) conducted interviews to investigate the impact of ChatGPT on education, while Rospigliosi (2023) highlighted both the advantages and potential drawbacks of ChatGPT in various domains, such as academic research, writing, publishing and authorship. For instance, some papers are comprised solely of letters, commentaries or editorials and may not have undergone a rigorous peer review. Thus, the employment of ChatGPT within the context of academia and higher education is a budding phenomenon currently being investigated.

Although ChatGPT has been lauded for its capacity to facilitate education by offering customised and adaptable learning tools (Lee *et al.*, 2023), some academics have expressed apprehension regarding the ethical implications of ChatGPT (Siegerink *et al.*, 2023). Additionally, there are concerns about its possible adverse effects on evaluation methods (Qian *et al.*, 2023), the development of students' advanced cognitive abilities (Kohnke *et al.*, 2023) and scientific authenticity (Grassini, 2023). Furthermore, scholarly works have been authored regarding the potential impact of ChatGPT on the field of education, as evidenced by Rospigliosi (2023). It is a common occurrence for scientific debates to arise when novel technologies are integrated into the educational sphere, as they tend to disrupt conventional practices and necessitate educators to adjust according to their potential advantages and disadvantages (Ray, 2023).

It has been acknowledged that students are significant stakeholders who desire to integrate ChatGPT into their tertiary education process. Because of this AI tool's recent launch, there is a shortage of information on the extent of students' receptivity towards this novel technology and its utilisation. The literature has identified a research gap that predominantly centres on university students' perspectives regarding ChatGPT and its prospects, particularly in the Sri Lankan context. Therefore, a research study is needed to examine students' acceptance of this technology and its determinants.

2. Literature review and theoretical framework

2.1 Literature review

The application of AI tools in education has a number of potentials. Many researchers have attempted to delineate the benefits of using such tools in academic settings. To cite, Onyema *et al.* (2022) explored the potential of machine learning (ML) in academic forecasting, highlighting its potential in predicting academic events and student learning styles, and found that ML algorithms help bridge traditional forecasting techniques, aiding in timely decision-making in education. However, according to Onyema *et al.* (2022), there are limitations such as errors, data acquisition and time-consuming issues that could affect their accuracy, but ML remains a promising forecasting technology for improving education quality. The progress in AI systems is transforming the education industry and how students gain knowledge and retrieve information (Rudolph *et al.*, 2023). Numerous educators have perceived ChatGPT as a promising prospect for revolutionising and enhancing future learning and research (Foroughi *et al.*, 2023). ChatGPT is highly advantageous for students as it enables easy access to information and knowledge, enhancing their learning process (Cotton *et al.*, 2023). Students can obtain feedback on their assignments using ChatGPT, improving their learning experience and reducing the workload for tutors. ChatGPT assists students in completing

their homework assignments and swiftly provides solutions to their inquiries. It possesses the ability to translate texts into several languages accurately.

It can be used as a valuable tool for enhancing students' writing skills (Rudolph *et al.*, 2023). Its conversational capabilities enable students to engage with the system and receive comprehensive assistance throughout their learning journey. Moreover, it can be used to evaluate the proficiency and intelligence of students. ChatGPT enables students to comprehend their development and performance, discover solutions and answers and tailor the quantity of assistance they offer based on their performance (Cotton *et al.*, 2023). The system produces content by using user input, which encourages self-directed learning among students.

Consequently, students exhibit higher levels of involvement and are more inclined to attain academic accomplishments (Susnjak, 2022). ChatGPT can potentially improve learning outcomes, and its educational advantages outweigh any potential drawbacks (Baidoo-Anu and Ansah, 2023). To examine the possible uses of ChatGPT in higher education, various areas can be considered, such as the generation of false citations by software (Cooper, 2023), the creation of assignments (Sullivan *et al.*, 2023) and assistance in essay writing (Crawford *et al.*, 2023). As universities consider the consequences of AI conversations, certain academic instructors have already integrated AI into their assignments to highlight its constraints and question the capabilities of the technology (Strzelecki, 2023). Universities are assessing the potential influence of ChatGPT on higher education instruction and learning. This technology's wide-ranging and potentially transformative capabilities are being considered (Lim *et al.*, 2023).

Numerous developing themes may be discerned by examining existing peer-reviewed literature on using ChatGPT in higher education and academia. The utilisation of ChatGPT is observed in several educational domains. Researchers have interviewed ChatGPT to inquire about its impact on education (Strzelecki, 2023). Additionally, some researchers have expressed issues and advantages concerning academic research, writing, publishing, authorship and other broad domains (Perkins, 2023). A few segmented studies have been conducted in the Sri Lankan context. For instance, Fairooz *et al.* (2023) conducted mixed research to understand students' use of AI tools and see their impact on academic integrity. Samarasinghe and Prasangani (2023) conducted a quantitative investigation on using ChatGPT English as a Second Language Learner (ESL) and found it has gained popularity among ESL students. We recognise that students are crucial stakeholders who wish to incorporate ChatGPT into their higher education process. As this AI tool was launched recently, there is limited knowledge regarding students' acceptance of this new technology and its use, especially in the Sri Lankan context. Therefore, we propose to conduct a study to investigate students' acceptance of this technology.

2.2 Theoretical framework

Numerous investigations have been conducted to better understand the incentives that prompt individuals to embrace information and communication technology (ICT) (Voicu and Muntean, 2023), especially in education. For instance, Onyema *et al.* (2020) conducted a study in Nigeria to understand the impact of emerging technologies on the performance of educators attached to tertiary institutions. They found that using emerging tools such as video-conferencing and e-learning platforms significantly improved the job performance of educators. The UTAUT2 has been widely recognised as a prominent theoretical framework. The UTAUT2 sought to integrate previously established theories in information technology (IT) research, focusing on user-centred analyses. Venkatesh *et al.* (2003) proposed the UTAUT2 model, suggesting several factors influence behavioural intention (BEH). These

factors include performance expectancy (PER), which relates to the advantages of using ICT for job performance; effort expectancy (EFF), which pertains to the perceived ease of using ICT; social influence (SOC), which refers to the impact of significant individuals in a person's life on their adoption of a specific technology; and facilitating conditions (FACs), which encompass digital infrastructure and organisational structure. FACs concern the availability of resources and support required to use a certain technology. Venkatesh *et al.* (2003) established a correlation between the perceived ease of use (PEU) construct derived from the technology acceptance model (TAM) and the EFF construct. Hedonic motivation (HED) refers to the favourable emotional reaction or feeling of satisfaction obtained from exploiting a certain technology. The habit of using a particular technology (HAB) concept refers to an acquired, automated response that may become more pronounced or altered over time because of technology use. HAB suggests that technology usage extends beyond mere familiarity acquired through experience and encompasses both automatic and spontaneous utilisation of the technology.

To the above constructs from UTAUT2 and TAM, the present study adds the variable of personal innovativeness (PI), which pertains to an individual's ability and willingness to adopt and use newly developed technologies in their daily routines (Agarwal and Prasad, 1998).

2.3 Performance expectancy

The construct, PER, refers to an individual's anticipation of how much a specific technology will enhance their performance in accomplishing particular tasks or objectives. This definition is consistent with that proposed by Venkatesh and Davis (2000). According to Axcell and Ellis (2023), PER refers to an individual's perception of the degree to which using technology will facilitate improvement in job performance. According to Malik *et al.* (2021), PER is important in adopting educational systems in academic environments. Multiple studies have provided evidence for the significant impact of PER on learners' intentions to adopt innovative educational technologies. Devisakti and Muftahu (2022) demonstrated the relationship in question within the Google Classroom framework.

Meanwhile, Lee *et al.* (2023) investigated this relationship in a mobile learning (m-learning) context. Within the framework of a research investigation evaluating the adoption and utilisation of ChatGPT among tertiary-level students, the term PER refers to the degree to which students perceive that using ChatGPT will amplify their scholarly achievements or efficiency. Thus, the following hypothesis is proposed:

H1. PER positively impacts students' intentions to use ChatGPT.

2.4 Perceived ease of use

The EFF factor was modified to PEU in the model for consistency within the technological research context. As Venkatesh *et al.* (2012) posited, PEU pertains to how individuals perceive that a specific system will not necessitate significant physical or cognitive exertion. Tung *et al.* (2007) established a direct correlation between PEU and the inclination to acquire knowledge online. The PEU construct significantly and positively impacts individuals' inclination to enrol in online courses. Furthermore, the finding above is corroborated by the outcomes of Voicu and Muntean's (2023) investigation, which involved a comparable number of participants from higher education institutions. They found evidence supporting the notion that PEU positively impacted the intention to use m-learning among postgraduate students. Based on the above discussion, we propose the following hypothesis:

H2. PEU positively impacts students' intentions to use ChatGPT.

2.5 Social influence

SOC pertains to an individual's perception of the expectation from important others to use a specific technology (Venkatesh and Davis, 2000). According to Lee *et al.* (2023), the degree of change in an individual's technology usage behaviour is brought about by others' influence. Observing individuals engaging in particular behaviours can lead to the perception that such behaviours are rational. Individuals depend on social structures and their associates to augment their inclination towards using technology. Several scholarly investigations (e.g. Kelly *et al.*, 2022; Shameem and Sanjeetha, 2021) have demonstrated that SOC is a crucial factor in shaping users' intentions to embrace technology in the education field. The phenomenon above has been exemplified in diverse settings, such as m-learning (Al-Emran *et al.*, 2020), e-learning platforms (Samsudeen and Mohamed, 2019) and learning-management systems (Sharma *et al.*, 2021). The present study uses the concept of SOC to denote how students perceive their peers, lecturers or other influential individuals within their social milieu as providing support or motivation for using ChatGPT. Accordingly, the following hypothesis is proposed:

H3. SOC positively impacts students' intentions to use ChatGPT.

2.6 Facilitating conditions

According to Venkatesh and Davis (2000), FACs refer to an individual's perception of the available resources and support required to use a specific technology effectively. It is my personal conviction that a system is backed by adequate organisational and technical infrastructure to facilitate its usage. FACs help the user adjust to the novel technological framework. According to Tewari *et al.* (2023), the availability of the Internet, technological support and institutional support are FACs that contribute to users' intentions to adopt new technology. Research has indicated that FACs play a pivotal role in shaping learners' BEH and are widely acknowledged as among the foremost factors in an individual's technology adoption (Samsudeen and Mohamed, 2019).

Furthermore, FACs have been recognised as a crucial element in the implementation of diverse educational technologies, including m-learning (Shameem and Sanjeetha, 2021), e-learning platforms (Tewari *et al.*, 2023) and augmented reality (Anders, 2023) within the context of higher education. Furthermore, FACs include the extent to which students perceive their access to the AI tool, given its high demand and their access to technical support and training in ChatGPT. Thus, the following hypothesis is proposed:

H4. FACs positively impact students' intentions to use ChatGPT.

2.7 Hedonic motivation

According to Venkatesh *et al.* (2012), HED refers to an individual's motivation to use a specific technology owing to its inherent enjoyment, pleasure, or novelty. Motivation is a significant factor in the acceptance and usage of technology across various contexts, as it relates to the personal satisfaction derived from using technology (Devisakti and Muftahu, 2022). Studies have demonstrated that the HED construct is a significant factor in adopting technology in diverse educational settings. Axcell and Ellis (2023) found that HED significantly influenced the utilisation of animation among university students. Tewari *et al.* (2023) and Lee *et al.* (2023)

reported its impact on adopting m-learning and e-learning platforms. Previous research has demonstrated the significance of this variable in forecasting the adoption of e-learning and mobile learning, as evidenced by studies conducted by Al-Emran *et al.* (2020). In this context, HED refers to the extent to which students perceive ChatGPT as an engaging and pleasurable platform and their level of satisfaction in exploring this novel AI technology. Therefore, the following hypothesis is proposed:

H5. HED positively impacts students' intentions to use ChatGPT.

2.8 Habit

According to Venkatesh *et al.* (2012), HAB refers to the extent to which an individual's utilisation of a specific technology is habitual or deeply ingrained as customary conduct. It is a series of learned actions that become automatic responses to specific situations. These actions are functional for achieving certain goals or end states. The literature has demonstrated that HAB significantly determines students' intentions to adopt technology in higher education. Scholarly sources have established that HAB is a robust indicator of technology usage (e.g. Sharma *et al.*, 2021). According to Foroughi *et al.* (2023), this is particularly evident within m-learning. Axcell and Ellis (2023) have observed the impact of HAB on the acceptance of e-learning platforms, while Lee *et al.* (2023) have highlighted HAB's significance in using certain platforms, such as Google Classroom. In the context of this investigation, HAB pertains to the extent to which students have systematically and consistently incorporated the use of ChatGPT into their academic routine. This could encompass variables such as the frequency and duration of usage and the extent to which ChatGPT has been assimilated into their operational processes. Thus, the following hypothesis is proposed:

H6. HAB positively impacts students' intentions to use ChatGPT.

2.9 Behavioural intention

BEH refers to people's intentions to transition from current to future systems. It is seen as an early stage of use behaviour (USE). It indicates whether users are willing to engage in a particular behaviour. Users' willingness to accept e-learning systems is determined by BEH (Tewari *et al.*, 2023). According to previous research (e.g. Venkatesh *et al.*, 2003) and in the context of e-learning systems (Samsudeen and Mohamed, 2019), people's actual use of electronic systems is directly and positively influenced by their intention to use such systems. Similarly, in the context of ChatGPT, the following is hypothesised:

H7. BEH positively impacts students' USE.

2.10 Personal innovativeness

The phenomenon of individuals demonstrating their tendency towards novel technology or innovation is commonly referred to as PI (Devisakti and Muftahu, 2022). It refers to an individual's level of conviction regarding their favourable inclination towards adopting novel technologies (Tewari *et al.*, 2023). An individual's PI in relation to new technologies is considered an inherent trait often associated with a propensity for risk-taking (Lee and Chan, 2007). Research investigating the implementation of diverse educational technologies has indicated that incorporating PI into the UTAUT model is crucial in higher education

settings. Devisakti and Muftahu (2022) found that PI significantly influenced the adoption of e-learning platforms. Strzelecki (2023) emphasised the significance of PI as a determining factor in using animation among university students. Similarly, Pillai *et al.* (2023) identified it as a crucial determinant in adopting lecture-capture systems. Furthermore, Al-Emran *et al.* (2020) revealed that PI was a crucial factor in the acceptance of m-learning. Within the framework of this study, PI refers to the degree of readiness students exhibit to adopt innovative technological tools such as ChatGPT, as well as their perceived capacity to acquire and proficiently use novel technological competencies. Thus, the following hypothesis is proposed:

H8. PI positively impacts USE.

2.11 Moderating effect of personal innovativeness

According to Cheng (2014), individuals with more PI are more likely to be considered innovators or early adopters. Innovators or early adopters are willing to tolerate technological inconveniences such as complexity or a lack of performance. They are motivated to explore new experiences because of their focus on the long-term advantages that innovation may offer (Devisakti and Muftahu, 2022). Therefore, individuals with a greater degree of PI are anticipated to cultivate more favourable attitudes towards novel technologies (Axcell and Ellis, 2023). According to Agarwal and Prasad (1998) and Schwartz (2003), the influence of individuals' perceptions of IT on their usage intentions can be moderated by PI. They suggested that individuals with a higher level of PI were more likely to exhibit a stronger intention to use IT, even when their perceptions of the technology were at a level similar to those with a lower level of PI. Axcell and Ellis (2023) revealed that using PI could regulate the inclination to use m-learning. Individuals who possess a tendency towards PI tend to derive pleasure from the stimulation of experimenting with novel technologies as a means of addressing possible challenges. Consequently, they may be more inclined to use such innovations to attain comparable enjoyable experiences (Rogers, 2004). Therefore, the present study deduces that PI can significantly enhance students' intentions to use ChatGPT. Therefore, the following is hypothesised:

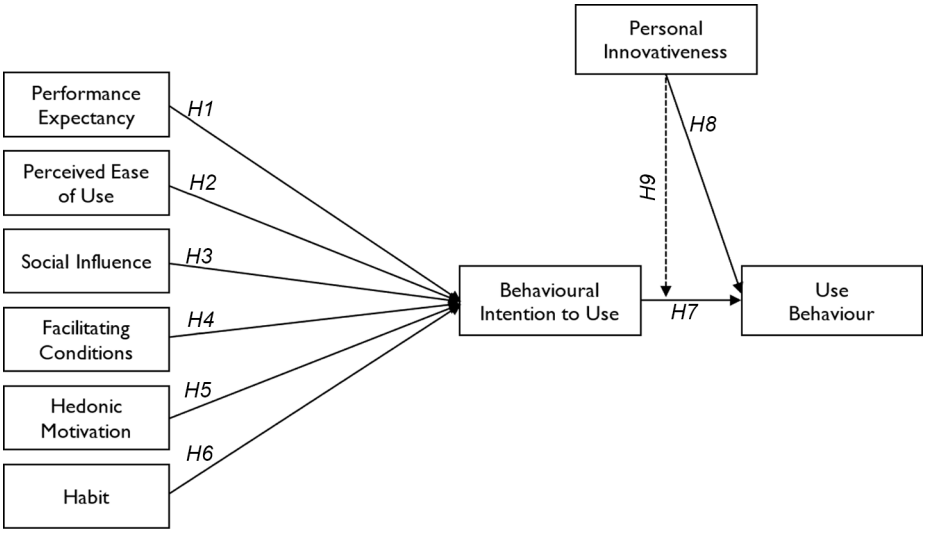
H9. PI moderates the relationship between the BEH to use ChatGPT and USE.

Based on the above discussion, the following model was derived (Figure 1):

3. Methodology

3.1 Instruments and measurement

This study examined Sri Lankan university students' ChatGPT use behaviour using a quantitative method based on a questionnaire survey with a cross-sectional time frame. Using the quantitative method, researchers can examine the connections between the variables included in their model and use the results to test their hypotheses. UTAUT2 (Venkatesh *et al.*, 2012) served as the foundation for the study's model. Appendix lists the items and their sources. The online questionnaire was designed to be as clear and objective as possible to facilitate responses from a wide range of people. We measured the responses on a seven-point Likert scale, with 1 representing "strongly disagree" and 7 representing "strongly agree".



Source: Adapted from Davis (1989), Devisakti and Muftahu (2022) and Venkatesh *et al.* (2012)

Figure 1.
Proposed model

3.2 Participants and procedure

A total of 17 Sri Lankan state universities' undergraduate students constituted the study's population. Given the lack of a population frame, a non-probabilistic snowball sampling technique was adopted. The sample size was meticulously established after consulting various literature sources. According to Hair *et al.* (2012), 10 data entries are required for each independent variable. According to Sekaran and Bougie (2016), a sufficient sample size for most research investigations is greater than 30 but less than 500. Studies based on structural equation modelling (SEM) almost always have a sample size of at least 200 responses, according to Kline (2011).

3.3 Data collection

Google Forms was used in the online survey and was shared across various social media sites and WhatsApp groups. The URL was also emailed to undergraduates enrolled in the Bachelor of Science in Management and IT program at the South Eastern University of Sri Lanka, where the current study's researchers work. These students were requested to share the link via WhatsApp and chat systems and email their known undergraduate contacts at other universities. Data were gathered during that time, which lasted from March 2023 until early May 2023. At the end of the time frame, a total of 514 completed questionnaires had been collected. All of the form submissions were imported into Excel from Google. Only 14 replies were screened and rejected because they were incomplete; the remaining 500 were retained for the analytical phase.

3.4 Data analysis

We adopted a two-stage approach using the partial least squares SEM (PLS-SEM) technique advocated by Anderson and Gerbing (1988) on SmartPLS 4 as well as artificial neural network (ANN) analysis on SPSS 27 to analyse and interpret the collected data. The first

step was to develop a measurement model using confirmatory factor analysis. Furthermore, SEM was used to evaluate the structural assumptions pertaining to the interconnectedness of all the constituent elements. A moderation analysis was performed to assess moderating effects within the research model. An ANN analysis was performed to obtain a more comprehensive understanding of the factors that drive undergraduate students in Sri Lanka to use ChatGPT.

4. Analysis

4.1 Demographic analysis

The respondents' demographic information is shown in Table 1. A total of 276 males (55.2% of the sample) and 224 females (44.8% of the sample) filled out the survey. Of these, 64 were in their first year (12.8%), 181 in their second year (36.2%), 197 in their third year (39.5%) and 58 in their fourth year (11.6%). On average, 4.8% of the students spend less than an hour online daily, 13.6% between 1 and 5 h, 42% between 6 and 10 h, 32.8% between 11 and 15 h and 6.8% more than 15 h per day. Interestingly, 76.2% of the students have smartphones, 2.8% have tablets, 19.6% have laptops and 1.4% have other gadgets.

4.2 Evaluation of the outer model

Measurement models evaluate the extent to which a set of measures has convergent and discriminant validity. The approach ensures that the indicators established to evaluate a certain construct accurately measure that construct. Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE) are commonly used to evaluate a PLS-path model's convergent validity. Cronbach's alpha is a robust measure that assesses the degree to which observed variables effectively represent latent variables. According to Hair *et al.* (2012), internal consistency and reliability have the utmost significance in terms of dependability.

Profile	Frequency	%
Gender		
Male	276	55.2
Female	224	44.8
Academic year		
First year	64	12.8
Second year	181	36.2
Third year	197	39.4
Final year	58	11.6
Internet usage		
Less than 1 h	24	4.8
1–5 h	68	13.6
6–10 h	210	42
11–15 h	164	32.8
More than 15 h	34	6.8
Usage – device		
Smart phones	381	76.2
Tablets	14	2.8
Laptops	98	19.6
Other gadgets	7	1.4

Table 1.
Respondents' profiles

Source: Summarised from collected data using Microsoft Excel 2021

Because of the demographic constraints associated with Cronbach's alpha, as Hair *et al.* (2012) discussed, the alternative approach presented here is deemed more suitable. Outer loadings are used in the calculations. Both Cronbach's alpha and CR may range from 0 to 1, with higher values indicating more reliability. The two measures convey the same meaning. Internal consistency reliability ranging between 0.60 and 0.70 is considered acceptable; those between 0.70 and 0.90 are considered good; and those less than 0.60 indicate a lack of internal consistency reliability (Hair *et al.*, 2012). Values greater than 0.95 are not desired as they indicate that all observed variables assess the same phenomena, rendering the construct invalid. The degree to which latent variables explain observable ones is measured by AVE. If the AVE values are more than 0.5, the latent variable partially explains the variance in the measurement (Fornell and Larcker, 1981). Henseler *et al.* (2016) suggest that the value of Dijkstra's Rho_A (Dijkstra and Henseler, 2015) for consistent dependability should be at least 0.7, in addition to the other three metrics.

Table 2 shows that the CR and AVE values are all greater than 0.5 and that Cronbach's alpha values are all higher than the criterion of 0.7 for each construct. Dijkstra's Rho_A (Dijkstra and Henseler, 2015) values are also satisfactorily above the 0.7 threshold. The model's convergent validity is thus established.

The degree to which a construct differs from others is demonstrated by its discriminant validity (Hair *et al.*, 2012). Discriminant validity ensures that a construct represents a special phenomenon not covered by other constructs. To ensure that the results of the hypothesised structural paths are legitimate and not the product of statistical anomalies, discriminant validity is established. Two metrics are suggested to evaluate discriminant validity. First, we consider how the indicators are loaded across (Table 3); second, we consider the Fornell and Larcker (1981) criterion. Outer loadings on related latent constructs should be larger than cross-loadings on other latent constructs in the first evaluation of a variable. The second consideration shows how closely the latent variable connects the square roots of AVE values. According to the highest correlations found with other variables, these square root values should be greater (Hair *et al.*, 2012).

Figure 2 shows the SmartPLS graphical output with outer loadings for the measurement model and path coefficients for the inner structural model.

Construct	VIF (inner model)	Cronbach's alpha	Composite reliability (rho_a)	Average variance extracted (AVE)
BEH	1.000	0.822	0.833	0.655
FAC	1.209	0.833	0.845	0.667
HAB	1.198	0.877	0.879	0.731
HED	1.196	0.864	0.881	0.711
PER	1.170	0.904	0.915	0.779
PEU	1.194	0.884	0.890	0.743
PI	1.371	0.88	0.882	0.675
SOC	1.289	0.774	0.825	0.596
PI × BEH	1.239	–	–	–
USE	–	0.772	0.780	0.686

Notes: BEH = behavioural intention; FAC = facilitating conditions; HAB = habit; HED = hedonic motivation; PER = performance expectancy; PEU = perceived ease of use; PI = personal innovativeness; SOC = social influence; USE = use behaviour
Source: SmartPLS 4 output

Table 2.
Reliability measures

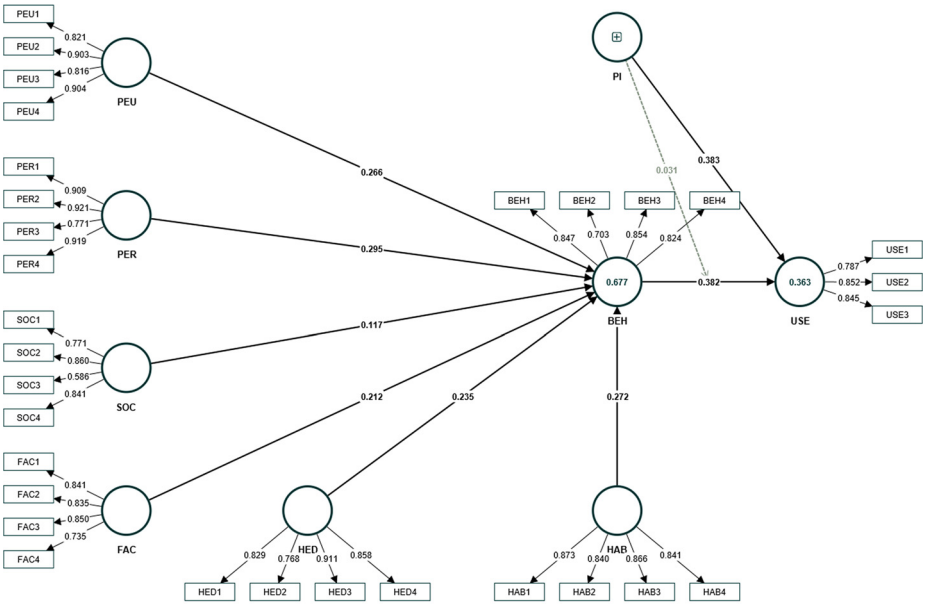
Items	BEH	FAC	HAB	HED	PER	PEU	PI	SOC	USE
BEH1	*0.847*	0.370	0.370	0.404	0.470	0.472	0.262	0.348	0.406
BEH 2	*0.703*	0.278	0.319	0.322	0.343	0.361	0.180	0.296	0.336
BEH 3	*0.854*	0.409	0.404	0.416	0.486	0.424	0.299	0.358	0.422
BEH 4	*0.824*	0.381	0.386	0.366	0.449	0.406	0.266	0.355	0.414
FAC1	0.395	*0.841*	0.121	0.223	0.202	0.164	0.237	0.150	0.166
FAC2	0.394	*0.835*	0.144	0.223	0.203	0.220	0.224	0.181	0.169
FAC3	0.373	*0.850*	0.100	0.191	0.132	0.171	0.214	0.161	0.223
FAC4	0.287	*0.735*	0.107	0.145	0.127	0.102	0.210	0.180	0.138
HAB1	0.396	0.125	*0.873*	0.102	0.155	0.117	0.176	0.240	0.382
HAB2	0.380	0.102	*0.840*	0.118	0.187	0.125	0.172	0.225	0.309
HAB3	0.417	0.156	*0.866*	0.112	0.154	0.105	0.173	0.313	0.399
HAB4	0.372	0.109	*0.841*	0.085	0.170	0.110	0.169	0.215	0.332
HED1	0.372	0.156	0.111	*0.829*	0.180	0.150	0.234	0.159	0.105
HED2	0.318	0.165	0.086	*0.768*	0.141	0.166	0.142	0.134	0.059
HED3	0.451	0.246	0.082	*0.911*	0.238	0.199	0.216	0.201	0.119
HED4	0.421	0.238	0.134	*0.858*	0.180	0.232	0.215	0.165	0.158
PER1	0.493	0.191	0.159	0.245	*0.909*	0.263	0.033	0.173	0.059
PER2	0.522	0.197	0.206	0.180	*0.921*	0.266	0.064	0.199	0.102
PER3	0.402	0.168	0.118	0.163	*0.771*	0.180	0.034	0.202	0.021
PER4	0.495	0.174	0.194	0.196	*0.919*	0.291	0.039	0.149	0.089
PEU1	0.417	0.172	0.107	0.193	0.246	*0.821*	0.003	0.208	0.106
PEU2	0.481	0.172	0.165	0.206	0.247	*0.903*	−0.007	0.301	0.146
PEU3	0.409	0.173	0.062	0.155	0.215	*0.816*	−0.011	0.194	0.097
PEU4	0.466	0.192	0.118	0.211	0.277	*0.904*	−0.012	0.248	0.108
PI1	0.296	0.224	0.207	0.216	0.069	−0.013	*0.829*	−0.068	0.438
PI2	0.231	0.239	0.162	0.201	0.002	−0.036	*0.831*	−0.121	0.390
PI3	0.271	0.213	0.140	0.203	0.041	0.023	*0.814*	−0.079	0.368
PI4	0.287	0.229	0.185	0.213	0.052	0.038	*0.810*	−0.093	0.376
PI5	0.158	0.208	0.105	0.131	0.020	−0.084	*0.823*	−0.148	0.395
SOC1	0.294	0.162	0.181	0.136	0.156	0.189	−0.112	*0.771*	0.090
SOC2	0.392	0.191	0.277	0.166	0.158	0.231	−0.055	*0.860*	0.131
SOC3	0.179	0.020	0.120	0.079	0.083	0.150	−0.117	*0.586*	0.011
SOC4	0.376	0.199	0.278	0.201	0.205	0.269	−0.104	*0.841*	0.095
USE1	0.364	0.176	0.307	0.119	0.080	0.103	0.340	0.095	*0.787*
USE2	0.408	0.176	0.351	0.108	0.055	0.080	0.405	0.097	*0.852*
USE3	0.439	0.182	0.375	0.109	0.064	0.146	0.438	0.099	*0.845*

Table 3.
Outer loadings of the constructs with their cross-loadings

Source: SmartPLS 4 output

The Fornell–Larcker criterion and outer loading measures are considered conventional methodologies when evaluating discriminant validity. We compare the correlations between the constructs (off-diagonal values) and the square root of the AVE for each construct using the Fornell–Larcker criterion presented in Table 4. The correlations between the components must be less than the square root of each construct's corresponding AVE for a measurement model to demonstrate discriminant validity. This suggests that the constructs' shared variance may not adequately capture their differences.

According to Henseler *et al.* (2016), using cross-loading and Fornell–Larcker criteria alone does not consistently provide conclusive evidence of diagnostic validity deficiencies over a wide range of research phenomena. A novel approach was devised using the heterotrait–monotrait (HTMT) correlation ratio values, whereby the matrix's most extreme value must not exceed 0.85.



Source: Generated from data collected by authors

Figure 2.
Output of the PLS algorithm

Table 4 shows that, according to the Fornell–Larcker criterion, the square roots of the AVE values are greater than their correlations with the latent constructs. The HTMT figures in Table 4 also support the assertion that the matrix's maximum value is 0.626, significantly less than the required value of 0.85. All three of these evaluations support the model's established discriminant validity.

4.3 Structural-model analysis and hypothesis testing

The PLS algorithm approach was used to compute the path coefficients of the hypothesised links and the endogenous variables' coefficients of determination. The bootstrapping approach was used to assess the importance of the results. Assessments of effect size (f^2) and predictive relevance were additionally conducted.

The variance inflation factor (VIF) must be between 0.20 and 5 to guarantee no collinearity problems with the inner model (Hair *et al.*, 2012). The VIF values for the predictor variables in Table 2 lie between 1.000 and 1.371, indicating no collinearity problems in the structural model.

The path coefficients for the suggested linkages were found to have high values when the structural model was evaluated. Statistical reliability was established by bootstrapping. In a two-tailed test with a 5% probability error, a *t*-value of 1.96 is considered statistically significant, as Hair *et al.* (2012) stated. Table 5 displays the results from the structural model, including the path coefficients and degree of significance. Consequently, it can be shown that BEH is significantly influenced by PEU, PER, SOC, FAC, HED, HAB and PI and that USE similarly influences BEH.

Figure 3 shows the inner model's path coefficients and corresponding *t*-values. This figure also shows the R^2 values for the constructs.

Construct	BEH	FAC	HAB	HED	PER	PEU	PI	SOC	USE
BEH	*0.809*								
FAC	0.448	*0.816*							
HAB	0.458	0.145	*0.855*						
HED	0.468	0.243	0.122	*0.843*					
PER	0.544	0.207	0.194	0.223	*0.882*				
PEU	0.516	0.206	0.133	0.223	0.286	*0.862*			
PI	0.315	0.271	0.202	0.241	0.049	−0.008	*0.820*		
SOC	0.420	0.204	0.292	0.198	0.203	0.278	−0.117	*0.772*	
USE	0.489	0.215	0.417	0.134	0.079	0.134	0.479	0.117	*0.829*
HTMT values									
BEH									
FAC	0.532								
HAB	0.538	0.168							
HED	0.548	0.278	0.140						
PER	0.626	0.235	0.216	0.248					
PEU	0.603	0.235	0.149	0.252	0.317				
PI	0.352	0.316	0.221	0.266	0.052	0.056			
SOC	0.504	0.235	0.334	0.227	0.236	0.326	0.162		
USE	0.610	0.266	0.503	0.161	0.093	0.159	0.577	0.137	
PI × BEH	0.234	0.163	0.049	0.127	0.083	0.035	0.460	0.032	0.234

Source: SmartPLS 4 output

Table 4. Fornell–Larcker criterion and HTMT values

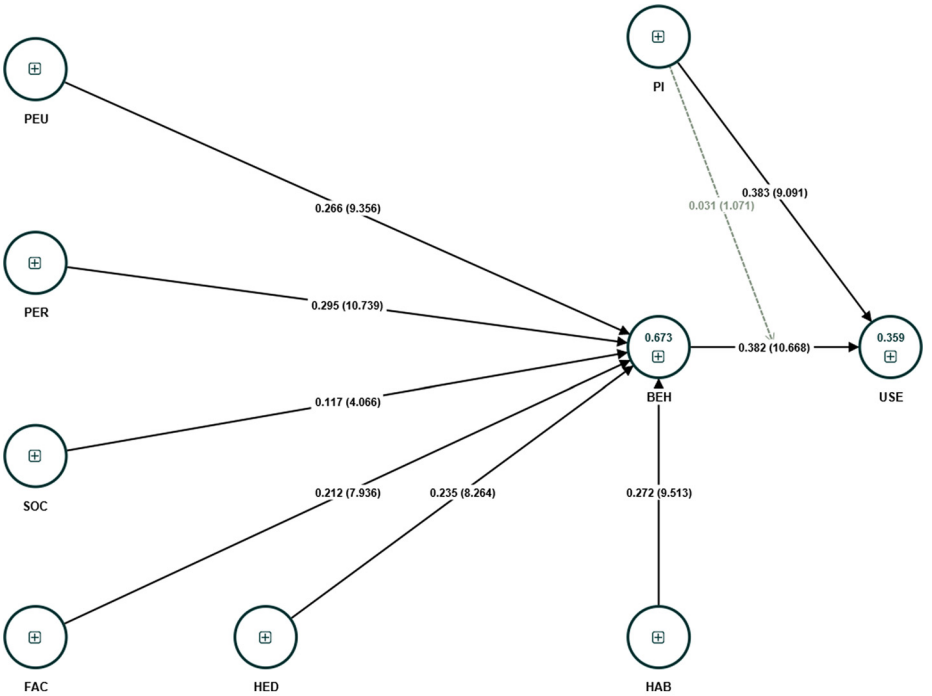
Hypothesised path	Original sample (O)	Sample mean (M)	SD (STDEV)	*t*-statistics	*p*-values	Results
BEH → USE	0.382	0.382	0.036	10.668	0.000	Supported
FAC → BEH	0.212	0.212	0.027	7.936	0.000	Supported
HAB → BEH	0.272	0.271	0.029	9.513	0.000	Supported
HED → BEH	0.235	0.236	0.028	8.264	0.000	Supported
PER → BEH	0.295	0.294	0.028	10.739	0.000	Supported
PEU → BEH	0.266	0.266	0.028	9.356	0.000	Supported
PI → BEH	0.383	0.385	0.042	9.091	0.000	Supported
SOC → BEH	0.117	0.118	0.029	4.066	0.000	Supported
(PI × BEH → USE)	*0.031*	*0.032*	*0.029*	*1.071*	*0.284*	*Not supported*

Source: SmartPLS output

Table 5. Path coefficients with *t*-statistics and *p*-values

The coefficient of determination (R^2) represents the predictability of the constructs in the proposed model. The model's predictive power is measured by the R^2, which computes the squared correlations between the estimated and actual values of the dependent variables (Henseler *et al.*, 2016). Figure 3 shows the R^2 values of 0.673 and 0.359 for the BEH and USE constructs, respectively. This means that PEU, PER, SOC, FAC, HED and HAB account for 67% of the variance in BEH for ChatGPT, and BEH and PI account for 36% of the variance in undergraduates' USE of ChatGPT in Sri Lankan universities.

The f^2 values range from 0.002 to 0.231, indicating a negligible moderation effect of PI. The SOC and FAC constructs had small effects, while the other constructs (BEH, HAB, HED, PER, PEU and PI) had medium effects (see Table 6).



Source: Generated from data collected by authors

Figure 3.
Inner model

Constructs	BEH	FAC	HAB	HED	Per	PEU	PI	SOC	USE	Effect
BER									0.206	Medium
FAC	0.123									Small
HAB	0.204									Medium
HED	0.151									Medium
PER	0.231									Medium
PEU	0.185									Medium
PI									0.176	Medium
SOC	0.035									Small
PI × BEH									0.002	Negligible

Note: The f^2 values, $f^2 \geq 0.02$, $f^2 \geq 0.15$ and $f^2 \geq 0.35$, represent small, medium and large effect sizes, respectively (Hair *et al.*, 2012)
Source: SmartPLS output

Table 6.
f^2 effect sizes

The predictive significance of the model was inferred using Stone–Geisser's Q^2 value (Geisser, 1974), which was computed using the PLS Predict function in SmartPLS 4. Table 7 presents the results. Tenenhaus *et al.* (2005) show that the model's predictive ability may be inferred from Q^2. Predictive relevance is indicated by a Q^2 value of more than zero, while a

Q^2 value of less than zero indicates the absence of predictive relevance. A Q^2 value between 0.02 and 0.15 indicates a weak effect, one between 0.15 and 0.35 indicates a moderate effect and one higher than 0.35 indicates a strong effect, as stated by Hair *et al.* (2012). Our findings indicate a Q^2 value for BEH of 0.666, which equates to a very high degree of predictive accuracy. The Q^2 result for USE was 0.267, indicating moderate predictive significance.

4.4 Moderation analysis

The study also assessed the moderating effect of PI on the relationship between BEH and USE, and the results showed no such effect (PI × BEH → USE). Although its path coefficient was 0.031, the *t*-value of 1.071 and *p*-value of 0.284 showed that the relationship was nonsignificant.

4.5 Artificial neural network analysis

ANN1 and ANN2, distinct AI models, were developed with unique designs and prediction objectives. ANN1 uses PER, PEU, FAC, SOC, HED and HAB to predict BEH, whereas ANN2 uses PI and BEH as independent variables to forecast USE. Table 8 presents the case-processing summary; Table 9 presents network information; Table 10 presents a model summary for ANN1 and ANN2; and Table 11 presents independent-variable importance. In this study, the MLP model was trained on a sample of 500 cases. Training and testing data sets are often used in machine learning to ensure a model's effectiveness; the model is trained on the training set and then tested on the testing set.

According to Table 8, ANN1 used most of the data during the training and testing phases, that is, 69.4% or 347 observations, leaving 30.6% or 153 observations for testing. ANN2 was trained on nearly the same number of cases or rows, 68% or 347 observations, and was tested on the remaining 32% or 160 observations.

Table 9 shows that the two models share a common structure, comprising an input layer, a hidden layer and an output layer. The ANN1 input layer included 6 nodes, each representing a different covariate (FACs, HAB, HED, PER, PEU and SOC). In ANN2, the input layer included 2 nodes, each representing a different covariate (PI and BEH). These covariates were standardised, a common practice in machine learning, to ensure

Table 7. Latent-variable prediction summary (PLS-SEM)

	Q^2 predict	RMSE	MAE	Effect
BEH	0.666	0.580	0.463	Strong
USE	0.267	0.860	0.691	Moderate

Source: SmartPLS 4 output

Table 8. Case-processing summary

		ANN1		ANN2	
		N	%	*N*	%
Sample	Training	347	69.4	340	68
	Testing	153	30.6	160	32
Total		500		500	

Source: SPSS output

		ANN1	ANN2
Input layer	Independent variables	FAC HAB HED PER PEU SOC	PI BEH
	Number of units	6	2
	Rescaling method for covariates	Standardised	Standardised
Hidden layer(s)	Number of hidden layers	1	1
	Number of units in hidden layer 1	5	4
	Activation function	Hyperbolic tangent	Hyperbolic tangent
Output layer	Dependent variables	BEH	USE
	Number of units	1	1
	Rescaling method for scale dependents	Standardised	Standardised
	Activation function	Identity	Identity
	Error function	Sum of squares	Sum of squares

Source: SPSS output

Table 9.
Network information

	ANN1		ANN2	
Training	Sum of squares error	59.414	Sum of squares error	113.584
	Relative error	0.343		0.670
Testing	Sum of squares error	23.480	Sum of squares error	49.471
	Relative error	0.255		0.563

Source: SPSS output

Table 10.
Model summary

Dependent	Independent	Importance	Normalised importance (%)
BEH (ANN1)	HAB	0.217	100.0
	PER	0.200	92.3
	HED	0.176	81.1
	PEU	0.170	78.5
	FAC	0.148	68.3
	SOC	0.089	41.0
USE (ANN2)	PI	0.621	100.0
	BEH	0.379	61.1

Source: SPSS output

Table 11.
Independent-variable importance

that all variables are on a similar scale and that no single variable dominates the model because of its scale. However, they diverge in the complexity of their hidden layers, with ANN1 featuring five units and ANN2 incorporating four units. Both models' activation and error functions are the hyperbolic tangent function and the sum of squares, respectively.

According to Table 10, exploring ANN1's and ANN2's performances revealed intriguing trends. ANN1 exhibited a lower sum-of-squares error (59.414) during training than ANN2 (113.584), suggesting a superior fit to the training data. In the testing phase, ANN1 outperformed ANN2, displaying a lower sum-of-squares error (23.480 vs 49.471).

The models also estimated the importance of each independent variable (see Table 11), indicating how much each variable contributed to the prediction of the dependent variable, BEH. The results indicated that HAB had the highest importance (importance = 0.217, normalised importance = 100%). Wong *et al.* (2022) drew similar conclusions on the use of ChatGPT. Following HAB, PER exhibited the second-highest importance (importance = 0.200, normalised importance = 92.3%) (Al-Sharafi *et al.*, 2023; Falwadiya and Dhingra, 2022). HED and PEU also showed high importance values of 0.176 and 0.170, with normalised values of 81.1% and 78.5%, respectively (Duc *et al.*, 2023; Faasolo and Sumarliah, 2022). FACs also demonstrated substantial importance (importance = 0.148, normalised importance = 68.3%). The SOC construct was found to have comparatively lower importance (importance = 0.089, normalised importance = 41%). Duc *et al.* (2023) and Wong *et al.* (2022) drew similar conclusions on the use of ChatGPT in ANN2; PI emerged as the most influential independent variable, with a normalised importance of 100%, while BEH also demonstrated significant importance, with a normalised importance of 61.1%.

5. Discussion

In this study, the researchers investigated the influence of variables generated from various viewpoints on BEH on the use of ChatGPT. According to the study's findings and those of other related research (Alshurideh *et al.*, 2023; Axcell and Ellis, 2023; Samsudeen and Mohamed, 2019; Tewari *et al.*, 2023), PER positively influences students' BEH to use ChatGPT. This shows that ChatGPT is valued by students as a tool to improve their learning. The study's findings also indicate that students' opinions of ChatGPT's utility are critical in deciding their engagement. Students are more likely to use ChatGPT if they believe it is helpful and important for their education.

Indeed, according to the study's findings, SOC has less of an impact on students' BEH to use ChatGPT. This implies that comments, suggestions and encouragement received from peers and teachers may impact a student's decision to use ChatGPT (Pillai *et al.*, 2023; Samsudeen and Mohamed, 2019; Shameem and Sanjeetha, 2021; Yoon *et al.*, 2015). The existence of social support may favourably impact how students view and feel about ChatGPT. Students are more likely to view ChatGPT as a useful tool for their learning when they obtain support and encouragement from their peers and teachers. Additionally, social support may provide students with a sense of security and certainty when using ChatGPT, which can strengthen their intention to use it.

According to the study's findings, FACs influence students' BEH to use ChatGPT less. This implies that students' decisions to use ChatGPT might be influenced by the availability of pertinent and modern materials and direction and support at the institutional level. Similar results from earlier studies have been reported as well (Foroughi *et al.*, 2023; Lee *et al.*, 2023; Pillai *et al.*, 2023; Shameem and Sanjeetha, 2021; Yoon *et al.*, 2015), supporting the idea that FACs are crucial for the adoption and usage of technology in educational contexts. Higher education institutions may encourage incorporating ChatGPT in the educational process by providing students with the necessary tools, such as access to ChatGPT, technical assistance, training and advice. These supportive environments can increase students' comfort level while using technology and remove any possible obstacles or difficulties. Institutions can help create a productive learning environment where students are inspired to use ChatGPT by ensuring access to the right tools and assistance. This

finding highlights the significance of institutional commitment and investment in providing the tools and resources required to promote the integration of ChatGPT in higher education settings.

According to the study's findings, students' BEH to use ChatGPT is favourably influenced by HED (Alshurideh *et al.*, 2023; Axcell and Ellis, 2023; Samsudeen and Mohamed, 2019; Tewari *et al.*, 2023). This implies that the happiness and pleasure experienced when using AI platforms and tools, such as ChatGPT, might be a powerful incentive for students to interact with them. The capacity of AI platforms and tools to offer innovative and engaging learning experiences makes them so appealing. ChatGPT's sophisticated features, such as NLP and conversational skills, may intrigue and excite students. The interactive and dynamic features of ChatGPT may help students learn more effectively and enjoyably, increasing their desire to use it. It is important to note that comparable findings from previous studies have concluded that HED influences the adoption and use of technology in various circumstances. These results suggest that when technology provides gratifying and rewarding experiences, individuals are more willing to use it. Higher education institutions may strive to create AI platforms and technologies that meet educational goals and offer a fun and interesting user experience by acknowledging the significance of HED. Higher levels of student engagement and desire to use ChatGPT in their learning processes can result from creating a good and enjoyable learning environment.

Similar study findings indicated that HAB was a major predictor of BEH using ChatGPT (Axcell and Ellis, 2023; Devisakti and Muftahu, 2022; Farrokhnia *et al.*, 2023; Malik *et al.*, 2021; Tewari *et al.*, 2023). One possible explanation is that if students develop a habit of using ChatGPT, they will likely do it frequently.

Indeed, the study's findings show that PI moderates the association between students' ChatGPT USE and the independent variable (BEH) (Axcell and Ellis, 2023; Malik *et al.*, 2021; Strzelecki, 2023; Tewari *et al.*, 2023). PI element has the greatest influence on USE, whereas the influence BEH has, albeit significant, is less significant compared to PI (Devisakti and Muftahu, 2022; Farrokhnia *et al.*, 2023; Tewari *et al.*, 2023). By including PI as a moderating variable, the study offers a more thorough knowledge of how individual characteristics might affect students' BEH to use ChatGPT in higher education institutions. It emphasises the importance of considering students' traits and openness to innovation when assessing their intention to embrace and use ChatGPT.

The study's conclusions may apply to higher education institutions. Institutions can create interventions and strategies to target particular groups of students who may have varying amounts of innovativeness by acknowledging the moderating influence of PI. To promote the adoption and use of ChatGPT among students, they may have to offer specialised training, assistance and resources.

The study underlines the significance of personal innovation as an independent and moderating factor in BEH. It advances our understanding of the variables that affect students' BEH to use ChatGPT in higher education. This information can help create and use successful promotional tactics to encourage the incorporation of ChatGPT in educational settings. The study's findings are relevant for institutional decision makers planning technology integration into learning and teaching processes. Understanding the factors preventing people from following through on their BEH to use ChatGPT will help these decision makers. Institutions may create strategies and interventions to overcome these obstacles and encourage the successful adoption and use of ChatGPT by recognising these hurdles. The study also provides information that teachers may use to help students from all backgrounds participate in technology-related learning. Teachers can adjust their instructions and assistance to fit various

student groups' unique requirements and preferences by being aware of the elements that affect students' BEH to use ChatGPT. This may result in a more diverse and productive learning environment for technology.

The proposed model, which considers several variables and emphasises the components that help students follow through on their BEH to use ChatGPT, is particularly pertinent at present. It offers advice for the specific student groups that are being targeted to help them form habits, increase awareness and actively participate in technological studies.

Institutions and instructors may actively promote students' interaction with technology and support their learning in this field by applying the lessons from this study. The results highlight the importance of delivering individualised education, fostering good habits and raising awareness among students, especially those needing extra assistance to benefit from technology-enhanced learning experiences properly. Overall, the study offers decision makers and educators timely and pertinent advice for supporting students' use of ChatGPT for educational purposes and encouraging their active participation in technological learning processes.

6. Conclusions

The study focused on ChatGPT's application in higher education and how it affected students' learning processes. The UTAUT2 model served as the study's framework, with additional elements including PEU as an independent variable and PI as a moderating variable. The study's findings demonstrated that various factors substantially impacted students' BEH to use ChatGPT for learning. These included HED (the enjoyment gained from using ChatGPT), PER (the belief that using ChatGPT would improve learning outcomes), PEU (the idea that using ChatGPT is simple), SOC (the weight of other people's recommendations), FACs (access to necessary resources and support) and HAB (repeated use of ChatGPT). The study also found that PI, demonstrating students' openness to accepting and exploiting new technologies, had a moderating impact. This demonstrates that students with higher degrees of personal creativity were likelier to use ChatGPT for learning.

When viewed holistically, the study provided illuminating data on students' behaviour when using ChatGPT to support their learning. It highlighted the importance of several factors in influencing students' BEH to use ChatGPT while underscoring the requirement to engage more students in using ChatGPT and enhance their learning performance by considering these factors.

The generalisability of the conclusions is constrained because snowball sampling was used. Because of the reliance on voluntary, self-reported replies in online surveys, sampling bias may make students more receptive to ChatGPT. Due to sampling bias and generalisability issues, among other limitations of the study, it is possible that the results do not fully represent all students. Future studies can use more representative sampling techniques and conduct longitudinal research. This study investigated the factors influencing the adoption of ChatGPT; future studies could focus on understanding the challenges and barriers that university students might face when adopting AI tools such as ChatGPT. Further, future studies can incorporate culture and organisational support while discussing the ethical considerations of using AI tools in educational settings and security issues as well. By overcoming these limitations, researchers can increase the reliability and applicability of their findings regarding evaluating students' intentions to use ChatGPT.

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Appendix

Table A1. Questionnaire items and their sources

Latent variables	Items	Sources
Perceived ease of use	*PEU1: I think using ChatGPT is simple to understand*	Al-Emran *et al.* (2020); Malik *et al.* (2021); Yoon *et al.* (2015)
	PEU2: I believe that ChatGPT's activities are transparent and simple to comprehend	
	PEU3: I don't think I'll have any trouble using ChatGPT	
	PEU4: I don't have to use a lot of mental effort to communicate with ChatGPT	
Performance expectancy	*PER1: I find that using ChatGPT improves my academic productivity*	Al-Azawei and Alowayr (2020); Venkatesh *et al.* (2012)
	PER2: I find that using ChatGPT improves my capacity for problem solving	
	PER3: ChatGPT might be helpful for my academic writing	
	PER4: I believe that using ChatGPT expedites my learning	
Social influence	*SOC1: The majority of my colleagues believe that I should learn ChatGPT*	Al-Azawei and Alowayr (2020); Alshurideh *et al.* (2023)
	SOC2: Those who have the power to affect my decisions believe I should use ChatGPT	
	SOC3: My instructors and lecturers promote ChatGPT usage that is moral	
	SOC4: The university generally endorses the moral usage of ChatGPT	
Facilitating conditions	*FAC1: I have the tools required to use ChatGPT*	Venkatesh *et al.* (2012); Thomas *et al.* (2013)
	FAC2: I am equipped with the knowledge required to use ChatGPT	
	FAC3: ChatGPT works with the tools I use	
	FAC4: I had access to assistance when I needed it to use ChatGPT	
Hedonic motivation	*HED1: ChatGPT use is joyful*	Al-Azawei and Alowayr (2020); Venkatesh *et al.* (2012)
	HED2: ChatGPT use is entertaining	
	HED3: I think using ChatGPT is fascinating	
	HED4: I enjoy using ChatGPT to learn as a form of amusement	
Habit	*HAB1: I have acquired the habit of using ChatGPT*	Venkatesh *et al.* (2012)
	HAB2: I am dependent on ChatGPT	
	HAB3: I have to use ChatGPT	
	HAB4: I have become accustomed to using ChatGPT	
Behavioural intention	*BEH1: I intend to use ChatGPT for educational purposes and other academic projects in an ethical manner*	Al-Azawei and Alowayr (2020); Venkatesh *et al.* (2012)
	BEH2: I will always make an effort to use ChatGPT for my coursework	
	BEH3: I anticipate using ChatGPT in the upcoming semester	
	BEH4: For my coursework and other obligations over the upcoming semester, I intend to use ChatGPT frequently	
Personal innovativeness	*PI1: I enjoy testing out cutting-edge informational technologies*	Agarwal and Prasad (1998); Lee *et al.* (2007)
	PI2: If I learned about it, I would look for opportunities to experiment with new information technology	
	PI3: I am frequently the first among my acquaintances to test out new informational technologies	
	PI4: I am receptive to fresh concepts and methods	
	PI5: I have faith in my capacity to pick up new skills	
Use behavior	*USE1: I regularly use ChatGPT*	Venkatesh *et al.* (2012)
	USE2: I frequently engage with ChatGPT for various academic tasks	
	USE3: My usage of ChatGPT is consistent and ongoing	

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