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Research Article

Higher education students' ChatGPT use behavior: Structural equation modelling of contributing factors through a modified UTAUT model

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ABSTRACT

Despite the increasing interest in artificial intelligence technologies in education, there is a gap in understanding the factors influencing the adoption of ChatGPT among Nigerian higher education students. Research has not comprehensively explored these factors in the Nigerian context, leaving a significant gap in understanding technology adoption in this setting. This study addressed this gap by investigating the predictors of students' behavioral intentions (BIs) and actual use behavior of ChatGPT through the lens of the unified theory of acceptance and use of technology 2 (UTAUT2) framework. A cross-sectional correlational research design was used to examine the relationships between extended UTAUT variables, BIs, and ChatGPT use behavior. A sample of 8,496 higher education students from diverse institutions in Nigeria participated in the study. The data were collected using the higher education students' ChatGPT utilization questionnaire, which assessed various factors, such as performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FCs), hedonic motivation (HM), habit (HB), BI, and ChatGPT use behavior. The findings reveal several significant predictors of students' BIs and actual usage of ChatGPT. PE, SI, HM, and HB were found to be significant positive predictors of BI, while EE and FCs were significant negative predictors. For ChatGPT use behavior, FCs, HM, HB, and BI were significant positive predictors, whereas PE and SI were significant negative predictors. BI mediated the relationships between several factors and ChatGPT usage behavior: positively for some (PE, SI, HM, and HB) and negatively for others (EE and FC). This study contributes to understanding the adoption of ChatGPT in higher education contexts. The findings highlight the importance of addressing usability issues, providing adequate support and resources, promoting a positive user experience, fostering habitual usage, and leveraging social networks to encourage adoption.

Keywords: artificial intelligence, chatbots, GenAI, large language models, technology use

INTRODUCTION

Artificial intelligence (AI) is a modern technology that has sparked international discussions and debates among scholars, particularly about the development of large-language models. AI refers to intelligent technological devices and software that can reason, absorb information, gather knowledge, interact, control, and distinguish between objects (AlAfnan et al., 2023). These AI applications have received much attention in the last couple of years. It has been documented that AI enables tutors to personalize learning and promote individualized education (Chen et al., 2020; Ouyang & Jiao, 2021), including classroom assessment (Owan et al., 2023a). There are different AI tools with promising utility values. However, one AI tool currently attracting global discussion among educational stakeholders and on the verge of changing the entire landscape of the education sector is the chat generative pre-trained transformer (ChatGPT).

ChatGPT is an AI tool that enables text generation based on user prompts. It is designed to understand natural language and generate intelligent and relevant answers to user queries. ChatGPT can improve writing because it can generate texts and summarize information, and outline (Ibragimov et al., 2025). Furthermore, it can be deployed to spot grammatical errors, thus enhancing comprehension (Halaweh, 2023). Other benefits of ChatGPT, include helping teachers and students generate human-like conversations (Rudolph et al., 2023), improving students' learning and critical thinking (Bitzenbauer, 2023), aiding language learning and translation (Ifelebuegu et al., 2023; Jeon & Lee, 2023), generating educational content (Perkins et al., 2023), facilitating classroom assessment (Gamage et al., 2023; Ofem & Chukwujama, 2024; Owan et al., 2023a), and serving as teaching assistants (Kuhail et al., 2023; Samara & Kotsis, 2024). Nevertheless, other scholars have identified challenges associated with using AI tools for academic purposes despite these benefits. These challenges include academic dishonesty and plagiarism (Cotton et al., 2023; Kleebayoon & Wiwanitkit, 2023), bias and unfairness (Ray, 2023), high costs for premium versions (William & Misheal, 2024), decreased creativity (Bissessar, 2023), and fear of job loss (Abayomi et al., 2021).

Due to students' perceptions of ChatGPT as useful (Limna et al., 2023), previous research continues to report high use of different AI tools among higher education students (Bissessar, 2023; Grájeda et al., 2023; Ouyang et al., 2022), despite the challenges discussed earlier. In Africa, students have a high awareness, acceptance and use of AI for various educational purposes (Ofem et al., 2024; Owan et al., 2025; Owolabi et al., 2022; William & Misheal, 2024). The high use of AI tools among higher education students makes it pertinent for studies to explore the factors predicting their use of AI (Nikolopoulou, 2025). This importance has prompted previous studies to identify factors associated with students' acceptance of ChatGPT using the unified theory of acceptance and use of technology (UTAUT) (e.g., Yakubu & Dasuki, 2019) and the extended UTAUT (e.g., Cai et al., 2023; Strzelecki, 2023). However, within Africa and Nigeria, this study seems to be the first or among the few to use the extended UTAUT model to examine the factors predicting higher education students' ChatGPT use behavior. The extended UTAUT model enables researchers to account for cultural differences that may impact technology acceptance and use behavior (Abbad, 2021; Hu et al., 2020). Understanding the unique factors that drive or inhibit the adoption of technology among Nigerian students allows for the development of tailored interventions and strategies to promote ChatGPT use effectively.

THEORETICAL AND CONCEPTUAL FRAMEWORKS

The UTAUT model was established by Venkatesh et al. (2003) as an extension of previous works associated with the elements of eight models, such as the theory of reasoned action, the technology acceptance model, the motivational model, the theory of planned behavior, the combined TAM and TPB, the model of PC utilization, social cognitive theory and innovation diffusion theory. The UTAUT comprises four main constructs: performance expectancy (PE), social influence (SI), effort expectancy (EE), and facilitating conditions (FCs) (Venkatesh et al., 2003). These constructs of UTAUT are the determining factors that directly affect the intention to use or accept any given technology.

However, Venkatesh et al. (2012) modified UTAUT to create UTAUT2, adding three additional constructs: hedonic motivation (HM), price value, and habit (HB). In this model, several key constructs interact to influence behavioral intentions (BIs) and usage behavior. According to the theory, performance and effort expectancies positively impact intention and behavior. SI and FCs similarly contribute to intentions and behavior.

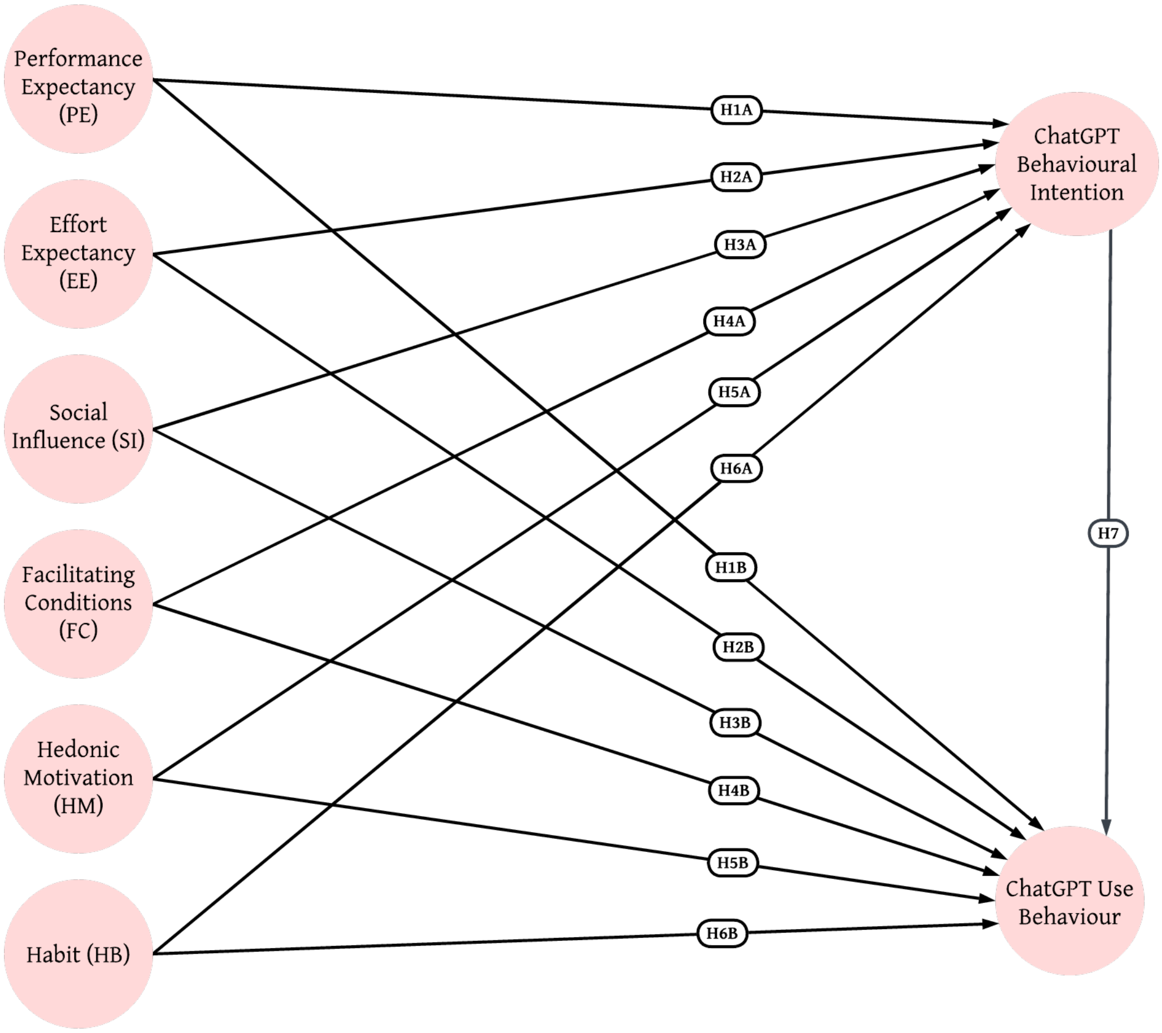

Figure 1. Conceptual model of this study based on the extended UTAUT model (Source: Authors' own elaboration)

Additionally, HM and price value influence intentions. HB, formed through repeated use, primarily affects behavior. The UTAUT2 has become a prominent theoretical model for understanding the factors influencing the adoption and use of new technologies among individuals (Strzelecki, 2023; Tamilmani et al., 2021). Based on the variables of the UTAUT2 model, the conceptual model of this study was developed, as shown in **Figure 1**.

Figure 1 shows that the predictor variables of the present study are PE, EE, SI, FCs, HM, and HB. The mediating variable is ChatGPT BI, whereas the outcome variable is ChatGPT use behavior. However, this study did not include price value as a predictor variable. Price value was excluded from this study because ChatGPT has a free version, making the inclusion of price value unimportant. Moreover, moderating variables such as age, sex, study program, and marital status were not considered in the present study since they were outside the scope of the study.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Relevant studies related to the present study are reviewed in line with the outlined predictors in the conceptual model (**Figure 1**).

Performance Expectancy

PE denotes the degree to which individuals believe that using technology will help them accomplish achievements in job performance or improve their performance in learning procedures (Venkatesh et al., 2003; Xiaofan & Annamalai, 2025). PE is similar to the perceived usefulness and ease of use adopted in the TAM (Davis, 1989). In different studies, PE has been shown to significantly impact individuals' intention to use technology (e.g., Abbad, 2021; Ali et al., 2022; Ayaz & Yanartas, 2020; Strzelecki, 2023). However, some studies have shown an insignificant influence of PE on BI (e.g., Bervell et al., 2021; Khalid et al., 2021; Kumar & Bervell, 2019). Moreover, a study by Macedo (2017) revealed an indirect influence of PE on UB. This means that there was no significant influence on PE on UB. These contradictory results from the studies reviewed lead to the fact that there is no generalized conclusion regarding the influence of PE on BI. As a result, additional empirical studies are needed to close these gaps from diverse perspectives, especially among higher education students who depend largely on large language AI models such as ChatGPT for academic activities. As a result, we formed the following hypotheses:

H_{1A}: PE significantly influences higher education students' BIs to use ChatGPT.

H_{1B}: PE has a significant direct influence on higher education students' ChatGPT use behavior.

Effort Expectancy

EE is the degree of ease or effort involved in using technology (Venkatesh et al., 2003). In the context of our study, EE refers to the degree to which undergraduates feel that using ChatGPT is quite easy and requires very little effort to operate. Many studies involving the UTAUT model (e.g., Chen & Hwang, 2019; Strzelecki, 2023) revealed that EE significantly affects the intention to use a given technology. However, other studies (e.g., Ali et al., 2022; Iskandar et al., 2020; Khalid et al., 2021; Shittu & Taiwo, 2023) did not find evidence to support the effect of EE on BIs. The disagreement among the cited studies suggests that research on EE and BI has been inconclusive, and newer empirical evidence is needed from diverse contexts and cultural perspectives to clarify the role of EE in BI, especially among student populations. The present study addresses this gap by examining the direct effect of EE on students' BI to use ChatGPT in higher education. Additionally, several studies have revealed that EE significantly influences UB (e.g., Suki & Suki, 2017; Venkatesh et al., 2003; Yakubu & Dasuki, 2019). While there seems to be a general conclusion from the studies reviewed on the influence of EE on UB, most of these studies were not conducted in Nigeria, creating a gap that needs to be filled. The current study, therefore, intends to fill these gaps by further examining the influence of EE on higher students' ChatGPT use behavior. As a result, the following hypotheses were formulated:

H_{2A}: EE has a significant direct influence on higher education students' BI to use ChatGPT.

H_{2B}: EE has a significant direct influence on higher education students' ChatGPT use behavior.

Social Influence

SI is the degree to which individuals perceive that people who are important to them believe they should use a new technology (Venkatesh et al., 2003). In this study, SI refers to the degree to which students perceive that peers, instructors, or key figures in their social circle will encourage them to use ChatGPT. Many studies using the UTAUT model (e.g., Shittu & Taiwo, 2023; Strzelecki, 2023; Yıldız, 2018) have revealed that SI significantly influences the intention to use a particular technology. In contrast, several studies (e.g., Abbad, 2021; Ali et al., 2022; Bervell et al., 2021; Iskandar et al., 2020; Khalid et al., 2021) have shown that SI has no significant impact on BI. The mixed findings among previous studies show disagreement regarding the impact of SI on BI, creating an evidence gap. The present study proposes to address such a gap by further exploring whether SI will predict students' BI in the context of Nigeria. On the other hand, a study by Macedo (2017) revealed that SI has a significant direct influence on UB, with BI serving as the mediator. Consequently, the following hypotheses were formulated:

H_{3A}: SI directly influences higher education students' BIs to use ChatGPT.

H_{3B}: SI directly influences higher education students' ChatGPT use behavior.

Facilitating Conditions

FCs show the resources and knowledge necessary to use a given technology. The UTAUT model proposes that the environment inspires or restricts technology adoption and usage (Venkatesh et al., 2003). Similarly, many empirical investigations (e.g., Faqih & Jaradat, 2021; Raza et al., 2022; Shittu & Taiwo, 2023; Yu et al., 2021) have provided ample evidence that FCs positively affect students' BI to use technology. However, opposing studies reveal that FC does not significantly impact BI (e.g., Ali et al., 2022; Alotumi, 2022; Nikolopoulou et al., 2021; Strzelecki, 2023). The disagreement on the relationship between FC and BI shows that research in this area remains inconclusive due to the evidence gap that such disparities create. This gap requires further research to advance the frontiers of knowledge regarding the link between FC and students' BI toward the use of technology, particularly in higher education systems of developing nations, such as Nigeria.

On the other hand, while some studies have shown a significant influence on FC on UB (e.g., Abbad, 2021; Chen & Chen, 2021; Tahir, 2023), others (e.g., Ali et al., 2022; Nikolopoulou et al., 2021; Strzelecki, 2023) have shown no significant influence of FC on UB. Based on the preceding evidence, some gaps exist due to the lack of generalizable conclusions. However, additional studies need to be conducted to determine the influence of FC on higher education students' ChatGPT UB. This approach is particularly useful in developing nations facing several challenges in ICT utilization (Owan et al., 2021). In line with this, we hypothesize the following:

H_{4A}: FC has a significant direct influence on higher education students' BI to use ChatGPT.

H_{4B}: FC has a significant direct influence on higher education students' ChatGPT use behavior.

Hedonic Motivation

HM is viewed as the pleasure and enjoyment resulting from the post-usage behavior of technology (Venkatesh et al., 2012). In this study, HM refers to the extent to which higher education students find the use of ChatGPT interesting, enjoyable, fun, and pleasurable. Several previous studies have revealed that HM positively influences technology acceptance and BIs (Ali et al., 2022; Azizi et al., 2020; Faqih & Jaradat, 2021; Hu et al., 2020). Specifically, Strzelecki (2023) reported that HM positively influences higher education students' BI to use ChatGPT. However, some studies (e.g., Ain et al., 2016; Raza et al., 2022) did not find that HM positively influences students' BI toward using technology. The literature on HM and BI use technology has yielded contrasting evidence, suggesting a need for further research to clarify the arguments among previous studies. The current study addresses this gap by investigating how HM predicts higher education students' BI toward using ChatGPT. Furthermore, several studies have revealed that HM significantly influences UB (Ali et al., 2022; Baptista & Oliveira, 2015; Venkatesh et al., 2012). Thus, we hypothesized the following:

H_{5A}: HM significantly influences higher education students' BIs to use ChatGPT.

H_{5B}: HM significantly influences higher education students' ChatGPT use behavior.

Habit

HB can be defined as the degree to which an individual tends to accomplish certain behaviors (Ali et al., 2022). More precisely, concerning the UTAUT model, Venkatesh et al. (2012) stated that HB is the level to which individuals tend to accomplish certain behaviors automatically because of their previous learning and experiences with a certain technology, such as ChatGPT, for their instruction. Several studies (such as Ali et al., 2022; Alotumi, 2022; Kumar & Bervell, 2019; Strzelecki, 2023; Tamilmani et al., 2019) have shown that HBs have a positive influence on students' BIs to use technology. However, other studies (such as Ain et al., 2016; Twum et al., 2022) have shown no significant influence of HB on BI to use technology. The literature review shows disagreement among previous studies on the direct effect of HB on BI. This disagreement creates an evidence gap warranting further studies. The present study addresses this gap by examining how HB directly predicts higher education students' BI to use ChatGPT in Nigeria. Additionally, several studies have revealed that HB significantly influences UB (Ali et al., 2022; Chen & Chen, 2021; Nikolopoulou et al., 2021). As a result, we hypothesized the following:

H_{6A}: HB has a significant direct influence on higher education students' BIs to use ChatGPT.

H_{6B}: HB significantly influences higher education students' ChatGPT use behavior.

Table 1. Demographic characteristics of the respondents

Demographic	Category	Frequency (N)	Percentage (%)
Age	Under 18	58	0.80
	18–24	3,096	36.40
	25–34	3,240	38.10
	35–44	2,088	24.60
Sex	Male	4,584	54.00
	Female	3,912	46.00
Program of study	Bachelor's degree	2,856	33.60
	Master's degree	2,256	26.60
	Doctorate	1,632	19.20
	OND	744	8.80
	HND	744	8.80
	NCE	96	1.10
	PGD	168	2.00

Behavioral Intention

BI refers to the extent to which individuals are willing to use a particular technology for a specific purpose (Venkatesh et al., 2003). BI is considered one of the primary dependent variables of the UTAUT model (Venkatesh & Davis, 2000). Such an intention may be useful in predicting actual behavior. Several studies have shown that BI significantly influences UB (e.g., Chen & Chen, 2021; Jawad et al., 2023; Petters et al., 2024; Strzelecki, 2023; Tahir, 2023). While there seems to be a general conclusion on the influence of BI on UB, these studies were not conducted in Nigeria and did not conduct with focus on ChatGPT. As a result, additional studies need to be conducted to determine the influence of BI on higher education students' ChatGPT UB in various contexts. Furthermore, only a handful of studies have used BI as a mediating variable connecting all other predictors to technology use behavior. Among these studies, BI has been shown to play a significant mediating role in linking PE, EE, FC, SI, HB, and HM to UB (Ali et al., 2022; Huang, 2023; Macedo, 2017; Strzelecki, 2023). Consequently, the following hypotheses were proposed:

H_7: BI significantly influences higher education students' ChatGPT use behavior (UB).

H_8: BI plays a significant mediating role in linking PE, EE, SI, FC, HM, and HB to UB.

METHODS

A cross-sectional correlational research design was adopted to investigate the direct and indirect relationships of extended UTAUT variables, such as PE, EE, SI, FCs, HM, and HBs, with higher education students' BIs and ChatGPT use behavior in Nigeria. This approach involved examining relationships among variables without intervention, providing insights into their connections without establishing causation (Owan et al., 2023b).

Participants

A total of 8,496 higher education students participated in this study. The eligibility criteria for participation included enrollment in any tertiary institution, encompassing colleges, mono-technics, polytechnics, or universities, irrespective of ownership status, private, missionary, state, or federal. The demographic profile of the respondents (**Table 1**) revealed that 0.8% of the total sample (n = 72) was under 18 years old. This group was followed by individuals aged 18 to 24 (n = 3,096, 36.4%). The next age group consisted of individuals aged 25 to 34, representing 38.1% (n = 3240). Individuals aged 35 to 44 comprised 24.6% of the respondents (n = 2,088). For sex, the results indicate that males account for 54.0% (n = 4,584), with females constituting 46.0% (n = 3,912).

Table 1 reveals that individuals enrolled in bachelor's degree programs constitute the largest group (n = 2,856), representing 33.6% of the total sample. Individuals pursuing master's degrees (n = 2,256) were the next, representing 26.6% of the sample. Notably, those in doctorate programs (n = 1,632) represented 19.2% of the total respondents. Additionally, students in the OND and HND programs were equally represented, each having 744 individuals, representing 8.8% of the respondents. However, individuals enrolled in the NCE

Table 2. Sub-scales in section 3 of the HESCUQ survey with sample items

Sub-scales	Sample items	References
PE	PE1. Interacting with ChatGPT helps me generate content more efficiently. PE2. ChatGPT enables me to achieve writing tasks that are important to me. PE3. Using ChatGPT enhances the quality of my written work. PE4. The features of ChatGPT contribute to my productivity in writing PE5. Using ChatGPT positively impacts the clarity of my written output.	Bin-Nashwan et al. (2023) & Shahsavar and Choudhury (2023)
EE	EE1. Interacting with ChatGPT is easy for me. EE2. I find it easy to learn how to effectively use ChatGPT. EE3. Generating content with ChatGPT requires little of my mental effort EE4. The user interface of ChatGPT is user-friendly. EE5. I can quickly become skillful in utilizing ChatGPT for content creation.	De Schryver (2023), Latif and Zhai (2024), Ma and Huo (2023)
SI	SI1. The opinions of lecturers can affect my decision to use ChatGPT SI2. I will use ChatGPT for writing if someone influential recommends it SI3. I feel pressure to use ChatGPT for content generation from my peers SI4. The approval of fellow students influences my decision to use ChatGPT. SI5. I am more likely to use ChatGPT if my professors endorse it.	Menon and Shilpa (2023) & Strzelecki (2023)
FC	FC1. I have access to the necessary resources to use ChatGPT for writing. FC2. Technical support for ChatGPT is readily available for me. FC3. I have the required knowledge to utilize ChatGPT for content creation. FC4. I can easily obtain assistance when facing challenges in using ChatGPT. FC5. There are no barriers to accessing the resources needed to use ChatGPT.	Cortez et al. (2024), Macedo (2017), & Strzelecki (2023)
HM	HM1. Using ChatGPT for writing is enjoyable for me. HM2. I find pleasure in creating content with ChatGPT. HM3. The interactive nature of ChatGPT makes it entertaining for me. HM4. I derive personal satisfaction from using ChatGPT to write assignments. HM5. ChatGPT makes writing fun for me.	Habibi et al. (2023), Ma and Huo (2023), & Macedo (2017)
HB	HB1. I use ChatGPT automatically without thinking much about it. HB2. It has become a habit for me to use ChatGPT in my writing routine. HB3. Using ChatGPT has become natural in all my writing tasks. HB4. I find myself using ChatGPT unconsciously sometimes. HB5. Using ChatGPT is ingrained in my daily habits as a valuable writing tool.	Ofem et al. (2024), Owan et al. (2023a), & Petters et al. (2024)
BI	BI1. I intend to use ChatGPT in my future writing tasks. BI2. I plan to continue using ChatGPT in all my writing routines. BI3. I intend to use ChatGPT to assist me in my research report writing BI4. I strongly desire to continue using ChatGPT for all my assignments. BI5. I am inclined to include ChatGPT as a valuable tool in my writing toolkit.	Ma and Huo (2023), Owan et al. (2023b), & Shahsavar and Choudhury (2023)
UB	UB1. I often use ChatGPT to generate ideas for my school assignments UB2. Using ChatGPT has become a regular practice for me. UB3. I often use ChatGPT to source information for my research report writing UB4. ChatGPT is a go-to tool for me when I need assistance. UB5. I routinely incorporate ChatGPT into my content creation process. UB6. I habitually use ChatGPT as a valuable writing tool in my daily activities	Macedo (2017), Salifu et al. (2024), & Strzelecki (2023)

and PGD programs constituted smaller proportions, with 96 individuals (1.1%) and 168 individuals (2.0%), respectively.

Instrument and Measures

An online survey titled higher education students' ChatGPT utilization questionnaire (HESCUQ) was utilized for data gathering. The researchers crafted the questionnaire via Google Forms. The questionnaire comprised three sections. The first section included a cover letter and a checkbox to secure written informed consent from the participants. Additionally, respondents were asked to provide their email addresses to enable tracking of multiple submissions. In the second section, respondents' demographic information, including age, sex, and current study program, was gathered. In section 3, information on the UTAUT2 constructs was collected, and the constructs were further divided into eight subsections, as summarized in **Table 2**. The items in section 3 were adapted from previous literature and modified to suit the specific context of this study. All the items were rated on a four-point scale ranging from strongly agree to strongly disagree.

Validity and Reliability

The initial draft of the HESCUQ was presented to seven independent professionals, including three psychometrists and four educational technologists, for face and content validity. The panel tasked with prioritizing the items measuring each domain and ensuring comprehensive coverage of domain requirements, provided quantitative grading of each item's clarity and relevance. Analysis of the experts' ratings revealed satisfactory ranges for item content validity indices (I-CVIs), spanning from .74 to .99 (for clarity) and .83 to .99 (for relevance). Items with I-CVIs less than .80 underwent revisions to enhance clarity, relevance, or both following established guidelines (Lawshe, 1975). Additionally, a focus group session involving 15 higher education students was conducted to gather feedback on the clarity of the items, response times, and potential ambiguities. Insights and suggestions provided by the participants resulted in the removal of two items, leading to a final questionnaire consisting of 40 items.

Furthermore, the researchers performed exploratory factor analysis utilizing an oblique (ProMax) rotation based on principal axis factoring extraction to analyze the instrument's underlying structure. Initially, an eight-factor solution was derived, but five dysfunctional items were discovered, such as UB2 (which loaded onto two different factors), FC5 (which did not load to any factor), EE3, SI1, and SI5 (with loadings below the recommended threshold of .40). After screening these two dysfunctional items, the analysis was repeated, and eight factors were extracted, cumulatively accounting for 54.28% of the sum of squared loadings. The KMO value of sampling adequacy was .926, and Bartlett's test of sphericity was significant, χ^2 (703) = 176922.96, $p < .001$. The factors were loaded according to the variables of the UTAUT2 theory. To mitigate common method bias, several steps were implemented. First, respondents were assured of anonymity to encourage candid responses. Additionally, careful attention was given to avoiding statements linking the dependent variable with the independent variables in proximity within the questionnaire. The presence of multiple factors suggests a lack of evidence for common method bias, indicating that the variance observed in the data is likely not solely attributable to a single factor (Macedo, 2017).

Ethical Considerations and Data Collection Procedure

Participation in this study was voluntary, with concerted efforts made to mitigate potential biases. Despite the involvement of human subjects, ethical clearance was waived per national regulations (Federal Ministry of Health, 2007). Before the data were collected, written informed consent was obtained from all the respondents, who were assured that their responses would be anonymized and aggregated to maintain integrity and confidentiality. Additionally, respondents were informed that their emails were collected solely to verify unique responses. Measures were implemented to safeguard data integrity, including storage on the principal investigator's personal computer and protection by a password to prevent unauthorized access. Furthermore, the respondents were duly informed in the cover letter that the collected data would undergo analysis and eventual publication as a journal article, after which the data would be securely deleted.

For this study, data were electronically collected through a Telegram group created for this purpose. Physical contact was made with different tertiary institutions in Nigeria to locate students across diverse departments. Upon obtaining students' contact information, a Telegram group was formed through mutual agreement, comprising 10,161 students. Subsequently, the questionnaire link was disseminated within this group. The data collection spanned from October 13, 2023, to February 14, 2024, during which 8,496 responses were received and inspected for analysis.

RESULTS

Measurement Model and Quality Criteria Assessment

The measurement model was assessed to examine the respective loadings of individual items to their respective factors. **Table 3** illustrates that each item within the model exhibits notably high factor loadings relative to their respective factors. Prior scholarly discourse posits that items with loadings exceeding 0.70 are preferable (Memon & Rahman, 2014; Owan et al., 2023b). **Table 3** shows that all item loadings surpassed this threshold, ranging from 0.722 to 0.889. At the scale level, both Cronbach's alpha reliability values exceeded 0.70 for almost all factors except SI, with a Cronbach's alpha reliability coefficient of 0.664. However, the composite reliability values exceeded 0.70 across all the constructs (ranging from 0.811 to 0.923), indicating

Table 3. Factor loadings, reliability, and convergent validity analysis results

Items	λ	α	CR	AVE	VIF	R^2	f^2	$Q^2_{predict}$
BI1	.73				1.58			
BI2	.82				1.98			
BI3	.78				1.79			
BI4	.84				2.12			
BI5	.81				1.86			
BI		.86	.90	.63	1.84	.458	0.16	0.46
UB1	.79				1.63			
UB3	.78				1.69			
UB4	.85				2.11			
UB5	.83				1.83			
ChatGPT UB		.83	.89	.66		.583		0.52
EE1	.75				1.69			
EE2	.81				1.74			
EE4	.75				1.55			
EE5	.81				1.48			
EE		.79	.86	.61	1.92		0.00	
FC1	.81				1.74			
FC2	.82				1.90			
FC3	.82				1.66			
FC4	.72				1.49			
FCs		.80	.87	.63	1.85		0.03	
HB1	.80				2.00			
HB2	.89				2.94			
HB3	.88				2.79			
HB4	.82				2.24			
HB5	.82				2.13			
HB		.90	.92	.71	1.87		0.09	
HM1	.80				1.95			
HM2	.76				1.66			
HM3	.79				1.86			
HM4	.80				1.73			
HM5	.85				2.26			
HM		.86	.90	.64	2.62		0.05	
PE1	.76				1.76			
PE2	.79				1.82			
PE3	.75				1.58			
PE4	.82				1.93			
PE5	.82				1.90			
PE		.85	.89	.62	2.02		0.00	
SI2	.82				1.24			
SI3	.75				1.31			
SI4	.72				1.37			
SI		.66	.81	.59	1.29		0.00	

robust internal consistency across the variables. Convergent validity within the measurement models was evaluated utilizing the AVE. An AVE value of .50 or higher is compelling evidence for convergent validity within a construct (Rönkkö & Cho, 2022; Owan et al., 2022).

As indicated in **Table 3**, convergent validity was established across all variables, with AVE values ranging from 0.589 to 0.705. It was imperative to detect any potential collinearity within the measurement and structural model, as this could introduce bias into the path coefficients. As depicted in **Table 3**, the outer variance inflation factors (VIFs) for all the constructs remained below the recommended threshold of 5.00 (Hair et al., 2017), spanning from 1.29 to 2.94. Similarly, the VIFs for the inner model also stayed below 5.00, ranging from 1.84 to 2.69 (refer to **Table 3**). This discovery suggested the absence of significant collinearity among the predictor constructs in the structural model.

Subsequently, we evaluated the proportion of variance in the endogenous variables explained by the exogenous variables to assess the model's in-sample model fit and predictive accuracy. As illustrated in **Table 3**, PE, EE, FC, SI, HM, and HB jointly accounted for 45.8% (R^2 = .458) of the variance in students' BI to use

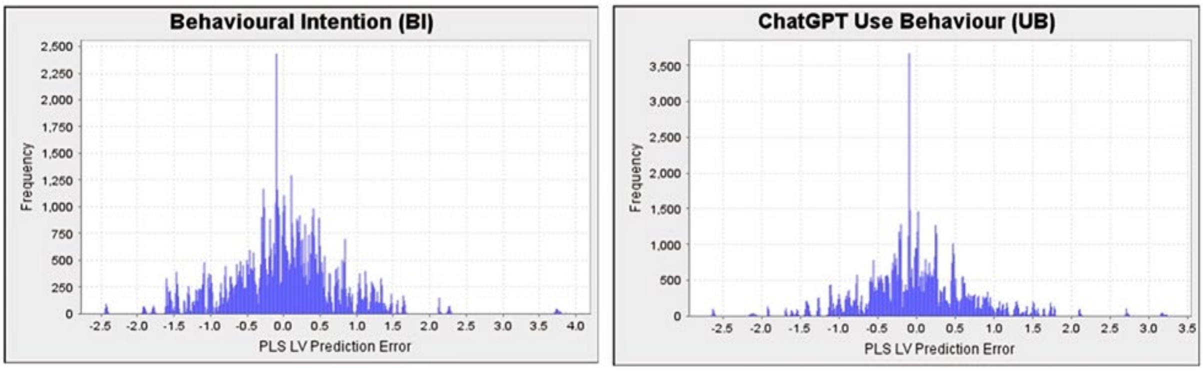

Figure 2. Histogram plots depicting the distribution of the endogenous variables (Source: Authors' own elaboration, 2025)

Table 4. Predictive model fit utilizing the RMSE obtained from the PLS-SEM and LM approaches

Items	PLS-SEM model		Linear model		RMSE difference (PLS-SEM–LM)
	RMSE	$Q^2_{predict}$	RMSE	$Q^2_{predict}$	
BI2	0.63	0.33	0.60	0.40	0.03
BI5	0.54	0.31	0.52	0.36	0.02
BI1	0.60	0.21	0.56	0.31	0.04
BI3	0.62	0.19	0.59	0.27	0.03
BI4	0.62	0.39	0.58	0.47	0.04
UB3	0.57	0.33	0.55	0.38	0.02
UB6	0.61	0.44	0.57	0.52	0.04
UB4	0.56	0.28	0.53	0.34	0.03
UB5	0.60	0.30	0.57	0.37	0.03

ChatGPT. Similarly, **Table 3** reveals that PE, EE, FC, SI, HM, HB, and BI cumulatively accounted for 58.3% (R^2 = .583) of the variance in students' ChatGPT use behavior. Thus, among Nigerian higher education students, 54.2% and 41.7% of the unexplained variance in BI and ChatGPT UB, respectively, can be attributed to other predictor variables. According to the established guidelines, the model's predictive accuracy is considered strong. Scholars have advocated acceptable R^2 values of .10 or higher (Hair et al., 2013). The f^2 values in **Table 3** range from 0.00 to 0.16, indicating small effect sizes (Cohen, 1988).

To evaluate the "out-of-sample" model fit, we applied "PLSpredict" with 10 folds and a single repetition. This approach replicates how the PLS model can be utilized for predicting a new observation, avoiding the use of averages across multiple models (Sharma et al., 2023). This method divided the dataset into training and holdout samples to estimate the model parameters and assess the predictive power separately. The training sample was used to estimate crucial parameters, while the holdout sample served predictive purposes (Shmueli et al., 2019). The $Q^2_{predict}$ values derived from the PLSpredict procedure were 0.46 (for BI) and 0.52 (for ChatGPT UB), all indicating positive values above zero (refer to **Table 3**). A positive $Q^2_{predict}$ value suggested good reconstruction, indicating the model's predictive relevance. Furthermore, when $Q^2_{predict}$ values are positive, the predictive error of PLS-SEM outcomes is lower than that when using mean values alone, demonstrating the superior predictive performance of PLS-SEM (Hair et al., 2022; Shmueli et al., 2019). A more detailed analysis of prediction errors was conducted to ascertain relevant prediction statistics. The graphical representations in **Figure 2** illustrate that the PLS-SEM errors follow a normal distribution. Consequently, the root mean squared error (RMSE) was favored over the mean absolute error (MAE) for evaluating the model's predictive capability, given the symmetric distributions in **Figure 2**.

Upon comparison of the RMSEs obtained from the PLS-SEM analysis with those from the naïve linear regression (LM) benchmark (as delineated in **Table 4**), it becomes apparent that the PLS-SEM analysis of the PLS-SEM procedure produced slightly larger RMSEs than the LM procedure; these differences were insignificant, ranging from 0.02 to 0.03. Given that the PLS-SEM incorporates a mediating variable, unlike the LM model, these minor deviations in the RMSEs may signify a predictive model, particularly when all other quality criteria lend sufficient support (Shmueli et al., 2019).

Table 5. Evidence of discriminant validity using the Fornell–Larcker and HTMT approaches

Factors	1	2	3	4	5	6	7	8
(1) BI	**0.80**	0.78	0.41	0.43	0.67	0.66	0.50	0.39
(2) UB	0.66	**0.81**	0.48	0.60	0.72	0.73	0.49	0.41
(3) EE	0.35	0.40	**0.78**	0.70	0.42	0.68	0.75	0.36
(4) FC	0.37	0.50	0.57	**0.79**	0.51	0.73	0.59	0.38
(5) HB	0.60	0.63	0.38	0.44	**0.84**	0.61	0.42	0.56
(6) HM	0.58	0.62	0.56	0.61	0.54	**0.80**	0.73	0.47
(7) PE	0.43	0.41	0.61	0.49	0.37	0.63	**0.79**	0.26
(8) SI	0.32	0.32	0.28	0.29	0.43	0.38	0.22	**0.77**

Note. **Bold** values along the diagonal are discriminant validity coefficients based on the Fornell-Larcker approach; values below the leading diagonal are correlations among factors; & values above the diagonal are HTMT discriminant validity coefficients.

Discriminant Validity

To ensure that theoretically unrelated variables were not strongly correlated, discriminant validity was evaluated. Various methods exist for assessing discriminant validity among constructs. One commonly used approach is the Fornell-Larcker method (Fornell & Larcker, 1981), which compares the square of the average variance extracted (AVE) with the correlations between a factor and other factors in the model (Owan et al., 2022). As depicted in **Table 5**, discriminant validity was confirmed for the seven constructs, as indicated by the bolded values along the diagonal (representing the square root of the AVE) being higher than the correlation of the diagonal. Another method used to verify discriminant validity is the heterotrait-monotrait ratio (HTMT), for which values should ideally be less than 0.90 (Owan et al., 2022). As demonstrated in **Table 5**, all HTMT values above the main diagonal are well below the 0.90 threshold, further supporting the evidence of discriminant validity from an alternative perspective.

Structural Model and Hypothesis Testing

This section examines the relationships between variables and tests specific hypotheses derived from the UTAUT2 theory, and in line with the conceptual model of this study (refer to **Figure 1**). The results are presented in two parts: the direct effects and the mediation effect. The inner model of a partial least squares structural equation model was utilized to determine the significant factors contributing to students' BI and ChatGPT use behavior. **Figure 3** and **Table 6** show that PE emerged as a significant positive predictor of BI ($\beta = .11$, $t = 9.48$, $p < .001$) and a negative predictor of ChatGPT use behavior ($\beta = –.05$, $t = 4.43$, $p < .001$) among higher education students. Thus, the first hypothesis was supported for both outcome variables. Second, EE had a significant negative predictive effect on higher education students' BI toward ChatGPT use ($\beta = –.04$, $t = 2.52$, $p < .05$). However, EE did not significantly influence students' ChatGPT use behavior ($\beta = .01$, $t = 0.57$, $p > .05$). Thus, the second hypothesis was supported for BIs, whereas it was not supported for students' ChatGPT use behavior.

Third, SI had a significant positive direct influence on students' BI in using ChatGPT ($\beta = .03$, $t = 2.27$, $p < .05$) but had a significant negative influence on students' ChatGPT use behavior ($\beta = –.03$, $t = 3.12$, $p < .01$). The third hypothesis was fully supported for both outcome variables (BI and UB). **Table 6** identified FC as a significant negative predictor of BI ($\beta = –.05$, $t = 3.56$, $p < .001$) and a positive predictor of UB ($\beta = 0.15$, $t = 12.50$, $p < .001$) among Nigerian higher education students. Consequently, the fourth hypothesis is supported by empirical evidence for both BI and UB. Moreover, HM positively and significantly influenced both BI ($\beta = 0.33$, $t = 19.95$, $p < .001$) and UB ($\beta = 0.23$, $t = 16.47$, $p < .001$). Similarly, HB has a significant positive influence on both BI ($\beta = 0.41$, $t = 36.92$, $p < .001$) and UB ($\beta = 0.26$, $t = 19.66$, $p < .001$). Therefore, this study's fourth and fifth hypotheses are supported by both outcome variables. Finally, BI was a significant positive predictor of ChatGPT use behavior among higher education students in Nigeria ($\beta = 0.35$, $t = 27.03$, $p < .001$).

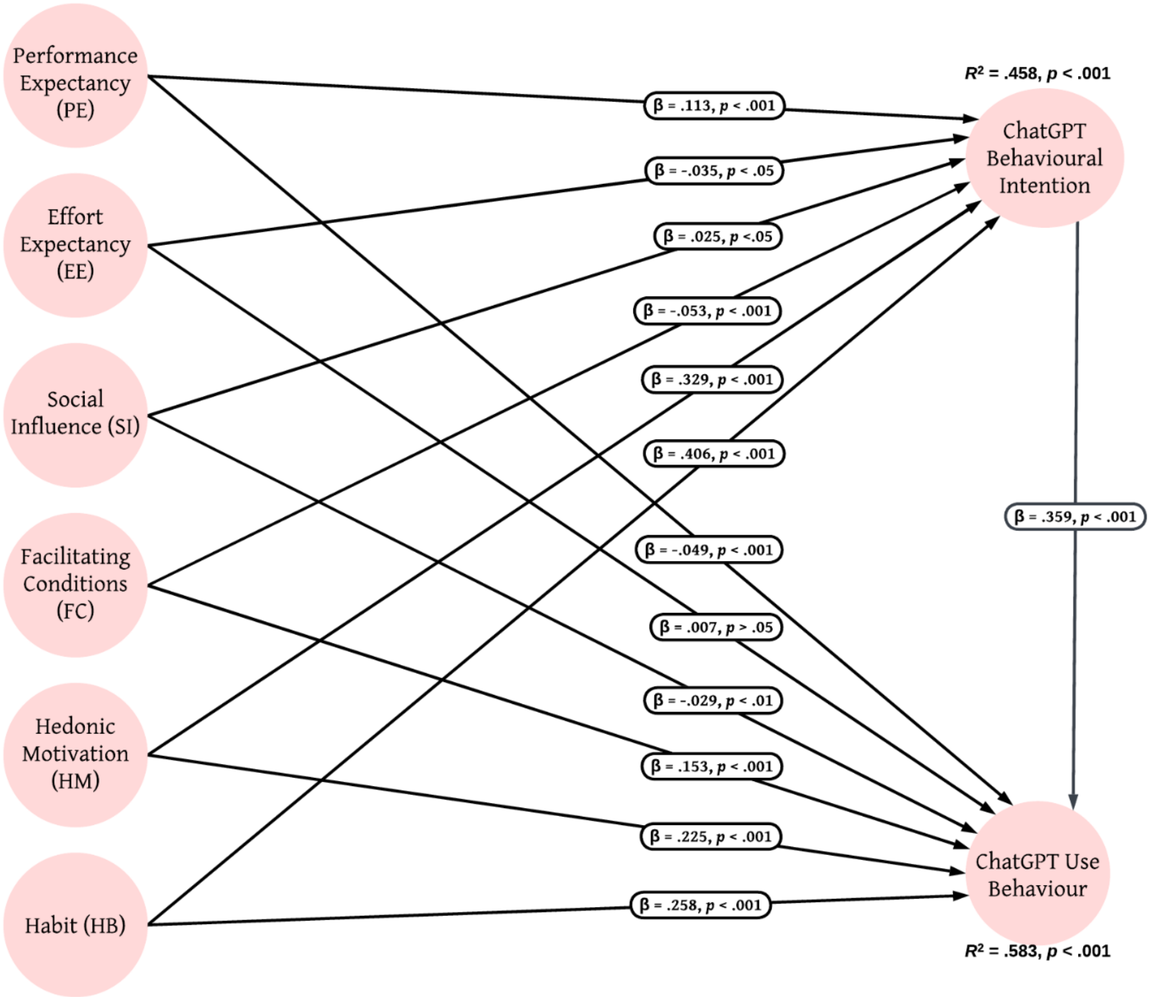

Figure 3. Structural relationships among the variables (Source: Authors' own elaboration, 2025)

Table 6. Direct effects of PE, EE, SI, FC, HM, and HB on BI and ChatGPT UB

Hypotheses	Mean	SD	B	95% CI	t	p	Decision
H_{1A}. PE → BI	0.11	0.01	.11***	.09, .14	9.48	.000	Supported
H_{1B}. PE → UB	–0.05	0.01	–.05***	–.07, –.03	4.43	.000	Supported
H_{2A}. EE → BI	–0.04	0.01	–.04*	–.06, –.01	2.52	.012	Supported
H_{2B}. EE → UB	0.01	0.01	.01	–.02, .03	0.57	.568	Not supported
H_{3A}. SI → BI	0.02	0.01	.03*	.00, .05	2.27	.023	Supported
H_{3B}. SI → UB	–0.03	0.01	–.03**	–.05, –.01	3.12	.002	Supported
H_{4A}. FC → BI	–0.05	0.02	–.05***	–.08, –.02	3.56	.000	Supported
H_{4B}. FC → UB	0.15	0.01	.15***	.13, .18	12.50	.000	Supported
H_{5A}. HM → BI	0.33	0.02	.33***	.30, .36	19.95	.000	Supported
H_{5B}. HM → UB	0.23	0.01	.23***	.20, .25	16.47	.000	Supported
H_{6A}. HB → BI	0.41	0.01	.41***	.39, .43	36.92	.000	Supported
H_{6B}. HB → UB	0.26	0.01	.26***	.23, .28	19.66	.000	Supported
H_7. BI → UB	0.35	0.01	.35***	.33, .38	27.03	.000	Supported

Note. ***Significant at .001 alpha level; **Significant at .01 alpha level; *Significant at .05 alpha level; SD: Standard deviation; CI: Confidence interval.

The Mediating Role of Behavioral Intention

This study tested for the mediating effect of BI on the relationship between each predictor and students' ChatGPT use behavior. **Table 7** indicates that BI significantly and positively mediated the relationship between PE and higher education students' UB (β = 0.04, *t* = 9.10, *p* < .001). **Table 7** shows that BI has a significant

Table 7. Mediation of BIs to link PE, EE, SI, FC, HM, and HB to higher education students' ChatGPT UB

Hypotheses	Mean	SD	B	95% CI	t	p	Decision
H_{8A}. PE → BI → UB	0.04	0.00	0.04***	.03, .05	9.10	.000	Supported
H_{8B}. EE → BI → UB	–0.01	0.01	–0.01*	–.02, .00	2.55	.011	Supported
H_{8C}. SI → BI → UB	0.01	0.00	0.01*	.00, .02	2.23	.026	Supported
H_{8D}. FC → BI → UB	–0.02	0.01	–0.02**	–.03, –.01	3.45	.001	Supported
H_{8E}. HM → BI → UB	0.12	0.01	0.12***	.10, .13	17.82	.000	Supported
H_{8F}. HB → BI → UB	0.14	0.01	0.14***	.13, .16	21.59	.000	Supported

Note. ***Significant at .001 alpha level; **Significant at .01 alpha level; *Significant at .05 alpha level; SD: Standard deviation; CI: Confidence interval.

negative mediating effect on the relationship between EE and students' ChatGPT UB (β = –0.01, t = 2.55, p < .05). Similarly, BI significantly and positively mediated the relationship between SI and students' ChatGPT UB (β = 0.01, t = 2.23, p < .05). Conversely, BI was found to be a significant negative mediator of the relationship between FC and students' ChatGPT UB (β = –0.02, t = 3.45, p < .001). **Table 7** also shows that BI significantly mediates the relationship between HM and students' ChatGPT UB (β = 0.12, t = 17.82, p < .001). Furthermore, BI significantly mediated the relationship between HB and students' ChatGPT UB (β = 0.14, t = 21.59, p < .001).

DISCUSSION

This study was undertaken to understand the factors contributing to higher education students' BIs to use and their actual ChatGPT use behavior. This study, grounded in the UTAUT2 model, revealed several meaningful findings. It was discovered that PE significantly and positively predicts higher education students' BIs but negatively and significantly predicts their ChatGPT use behavior. This finding means that students who believe that ChatGPT can be helpful for learning may be more likely to intend to use it because they see its potential benefits. This aligns with the findings of other studies showing that PE is a key driver of technology adoption (Ali et al., 2022; Shittu & Taiwo, 2023; Strzelecki, 2023). However, students with high PE might also be aware of the potential downsides of ChatGPT, such as plagiarism or overreliance. This awareness could create anxiety or ethical concerns that deter them from actually using it despite their initial positive expectations. Another reason for the negative prediction of PE on UB is that high PE could reflect initial optimism, but students might encounter difficulties integrating it into their learning process, leading to discouragement and lower actual use.

It was also discovered that EE has a significant negative predictive effect on students' BI to use ChatGPT. However, EE did not significantly influence students' ChatGPT use behavior positively. This finding means that students with high EE (who anticipate high effort in using ChatGPT) might be less likely to intend to use it. This finding does not support the finding of Strzelecki (2023) that EE has a significant positive effect on the intention to use a given technology. These findings also disagree with those of other studies documenting that EE does not significantly influence BI when different technologies are used (Iskandar et al., 2020; Nikolopoulou et al., 2021; Shittu & Taiwo, 2023). Despite the variations that may have been due to contextual differences, the current study's findings can be attributed to concerns about learning a new tool, navigating its interface, or understanding its capabilities. Students with heavy workloads or limited time might perceive using ChatGPT as an additional, unnecessary effort compared to existing study methods. Moreover, if students associate high effort with potentially achieving subpar results or wasting time using ChatGPT ineffectively, this could deter their initial willingness to try it. This may explain why EE had a significant negative influence on higher education students' BIs to use ChatGPT in the present study.

On the other hand, the positive influence of EE on higher education students' ChatGPT use behavior means that despite initial concerns about effort, students who have a strong underlying motivation for using ChatGPT (e.g., struggling with a specific task, seeking new learning methods) might still try it, even if they perceive it as effortful. This finding does not corroborate previous research showing that EE significantly influences UB (Suki & Suki, 2017; Yakubu & Dasuki, 2019). One possible reason for these findings is that EE might be relevant when first encountering ChatGPT, but as students gain skills and experience, their perceived effort could decrease, leading to actual use despite the initial negative prediction. However, the nonsignificant strength of the positive influence is attributable to the fact that the study did not comprehensively capture ChatGPT usage, such as frequency, duration, or specific tasks students used the AI tool to accomplish. Thus, the findings suggest that high-effort tasks might be avoided while simpler applications with perceived benefits might still be undertaken.

Third, SI significantly and positively predicted students' BI toward ChatGPT use. Conversely, SI significantly and negatively influences students' ChatGPT UB. The positive direct influence on BI aligns with the findings of previous studies (e.g., Shittu & Taiwo, 2023; Strzelecki, 2023; Yıldız, 2018) but disagrees with the findings of other studies (e.g., Ali et al., 2022; Nikolopoulou et al., 2021). These findings can be attributed to factors such as the bandwagon effect, information sharing, and fear of missing out. Students might be more inclined to try ChatGPT if they see others (peers, influencers) using or endorsing it. This social proof can create a sense of legitimacy and reduce perceived risks. Second, positive experiences or recommendations shared by others can spark students' interest in exploring the potential benefits of ChatGPT for learning or completing tasks. Moreover, students might feel pressured to use ChatGPT if they perceive it as a popular or trending tool among their peers, fearing that they might be disadvantaged if they do not try it. On the other hand, the significant negative influence of SI on students' ChatGPT UB is attributable to privacy concerns, negative experiences, or overblown expectations (Choudhury & Shamszare, 2023). If friends or peers express worries about the data privacy or misuse associated with ChatGPT, students might become hesitant to actually use it despite their initial interest. Second, hearing about other people's negative experiences with ChatGPT could deter students from trying it themselves. Moreover, exaggerated positive portrayals of ChatGPT's capabilities on social media could lead to disappointment and discourage actual use if students' expectations are unmet.

This study identified FCs as a significant negative predictor of BIs and a positive predictor of students' ChatGPT use behavior. The negative influence of FC on BI, as revealed in this study, does not align with the findings of two strands of studies: those reporting a significant positive influence of FC on Bi (e.g., Faqih & Jaradat, 2021; Raza et al., 2022; Shittu & Taiwo, 2023) and those that document no significant effect of FC on students' BI about the use of a given technology (e.g., Ali et al., 2022; Alotumi, 2022; Nikolopoulou et al., 2021; Strzelecki, 2023). Nevertheless, as revealed in this study, the negative direct influence of FC on students' BIs to use ChatGPT may be attributed to various factors, including perceived redundancy, overconfidence, or fear of complexity. The findings suggest that students might be less inclined to use ChatGPT if they perceive existing resources and technology (e.g., libraries, online learning platforms) as adequate and able to meet their needs. This finding suggested that FC might act as a perceived substitute for ChatGPT. Second, strong FC (implying that resources and support are readily available) could lead to overconfidence in students' ability to complete tasks without ChatGPT. If strong FC creates a perception of a complex ecosystem of tools and support structures surrounding ChatGPT, students might be intimidated and less likely to intend to use it due to concerns about navigating this complexity. In contrast, the positive and significant direct effect of FC on students' ChatGPT use behavior aligns with the findings of the extended UTAUT model (Venkatesh et al., 2012) and may be attributed to factors such as reduced barriers, increased confidence, exploration and experimentation. When students encounter challenges or limitations related to existing resources, strong FC (easily accessible support, tutorials, etc.) can facilitate overcoming those barriers and encourage them to try ChatGPT as a solution. Second, readily available support and resources might alleviate concerns about using ChatGPT effectively, leading students to engage with it despite not initially intending to do so.

Furthermore, this study revealed that HM positively and significantly influenced both BI and ChatGPT UB among higher education students in Nigeria. This finding is interesting and aligns with current research on technology adoption. Previous literature has shown that HM positively influences BI about the use of a given technology (Ali et al., 2022; Azizi et al., 2020; Hu et al., 2020). These findings also support the findings of Strzelecki (2023) that HM has a positive influence on higher education students' BI to use ChatGPT. However, these findings contrast with the findings of other studies reporting an insignificant positive influence of HM on students' BI with the use of technology (Ain et al., 2016; Raza et al., 2022). The positive influence of HM suggests that students motivated by fun, entertainment, or curiosity surrounding ChatGPT's capabilities might be more likely to intend to use it and engage with it due to the perceived enjoyable experience. The novelty and potential for exploring new ways of learning or completing tasks offered by ChatGPT could attract students to the hedonic experience of trying something different.

This study further revealed that HB significantly and positively influences both the BI and ChatGPT UB of higher education students in Nigeria. These findings align with previous research identifying HB as a significant predictor of BI (Ali et al., 2022; Alotumi, 2022; Strzelecki, 2023). However, these findings do not support the findings of other studies that found no significant influence of HB on BI to use technology (Ain et al., 2016; Twum et al., 2022). Despite the debate among previous researchers, the present study's findings are not surprising because frequent use of ChatGPT can solidify it as a regular part of students' study routines, increasing their likelihood of using it and doing so without much conscious thought. Second, once ChatGPT becomes habitual, students might require less effort to consider or decide whether to use it when faced with certain tasks or challenges, leading to more frequent automatic usage. Third, a HB can be driven by the belief that ChatGPT facilitates specific tasks or learning processes more efficiently than alternative methods, encouraging continued use.

It was further discovered that BI is a significant positive predictor of ChatGPT use behavior (UB) among higher education students in Nigeria. This finding is unsurprising since intention is a precursor to action (Alkhowaiter, 2022; Baluku et al., 2020; Camilleri, 2024). This study confirmed that a student's desire to use ChatGPT (intention) directly translates into them using it. This finding is consistent with the UTAUT theory (Venkatesh et al., 2003), which proposes that BI is useful in predicting actual behavior. Moreover, a long list of previous studies agrees, in their findings, that BI has a significant influence on UB (Abbad, 2021; Jawad et al., 2023; Petters et al., 2024; Strzelecki, 2023; Tahir, 2023), which highlights intention as a key driver of behavior (Owan et al., 2023b). In addition, positive intentions suggest underlying motivations that drive students toward ChatGPT, such as perceived benefits, such as improved learning, efficiency, or novelty.

BI was found to have a significant positive mediating effect on the relationships between PE, SI, HM, and HB and students' ChatGPT use behavior. These findings suggest that students' intention to use ChatGPT plays a central role in translating these various influences into actual usage. This finding aligns with the findings of Owan et al. (2023b), revealing that willingness is a positive mediator in the relationship between awareness and students' utilization of Facebook for research data collection. This means that BI acts as a "filter" through which the other factors influence actual use. The findings of this study imply that students may consider various factors, such as PE, SI, HM, and HB, but ultimately, their decision to use ChatGPT hinges on their intention to do so. This is unsurprising because BI reflects a conscious thought process (Cai et al., 2021; Zhu et al., 2023), where students weigh the pros and cons of using ChatGPT for specific tasks or situations. This intention then dictates whether they engage with the tool. Moreover, strong intentions are often fueled by motivation and a willingness to put in effort (Tiwari et al., 2022; Yamini et al., 2022). This translates into students actively seeking out and using ChatGPT despite potential challenges or barriers. In contrast, it was discovered that BI has a significant negative mediating effect on the relationship between EE and FC and students' ChatGPT behavior. These findings could mean many things. This could mean that students with high EE (perceiving using ChatGPT as effortful) might initially have a weaker intention to use it, even if they believe it could be beneficial. This negative intention becomes a barrier to actual usage despite potentially supportive FCs. Low confidence in using ChatGPT effectively or low motivation to overcome perceived effort could lead to discouraged intentions, even if FCs offer support. This translates to a reluctance to use the tool despite its potential. Students concerned about difficulty navigating FC (e.g., finding tutorials and receiving technical support) might have a diminished intention, even if they see the potential benefits of ChatGPT. This intention then reduces their likelihood of actually using it, regardless of available support.

Implications of the Findings for Research, Theory, and Practice

The study's findings offer significant implications for research, theory, and practice in higher education students' utilization of ChatGPT within the Nigerian context. First, the identification of BI as a mediator between several key variables—namely, PE, SI, HM, and HB, and ChatGPT use behavior underscores the importance of understanding the cognitive processes underlying technology adoption. This finding suggests avenues for further research to explore other mechanisms through which these variables influence BIs and subsequent actual behavior, thereby contributing to a more comprehensive understanding of technology adoption dynamics. Moreover, the study's findings regarding the differential effects of EE and FC on BI and actual behavior underscore the complexity of the adoption process. This highlights the need for future research to explore potential moderating factors that may influence these relationships. Such investigations could enrich existing theoretical frameworks and inform the development of models of technology adoption tailored to specific contexts.

Theoretically, the study underscores the necessity of extending existing models, such as the UTAUT, to better capture the intricacies of technology adoption within diverse contexts such as higher education in Nigeria. This may involve incorporating additional variables, refining existing relationships, or integrating insights from complementary theoretical perspectives such as the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), or Uses and Gratifications Theory. Moreover, the importance of HM (enjoyment) suggested that ChatGPT might appeal beyond purely utilitarian benefits. The study also strengthens the understanding of BI as a crucial mediator in technology adoption models, highlighting its role in translating beliefs and attitudes into actual behavior. The findings emphasize the need to consider contextual factors such as cultural influences and infrastructure limitations when applying UTAUT in diverse settings.

From a practical standpoint, the findings offer actionable evidence for stakeholders promoting ChatGPT adoption among higher education students in Nigeria. Tailored interventions can enhance PE, SI, HM, and HB formation while addressing barriers related to EE and FC. This could entail providing user-friendly interfaces, clear instructions, and technical support to mitigate challenges associated with usability and access. Furthermore, efforts can be directed toward fostering positive user experiences through gamification, personalization, and content customization. Addressing concerns about EE and FCs might involve improving internet access, providing technical support, and ensuring user-friendly interfaces. Practitioners can enhance engagement and promote sustained adoption by emphasizing the hedonic aspects of ChatGPT use and creating enjoyable user experiences. Moreover, equipping faculty members with knowledge about student motivations and challenges related to ChatGPT use can help them adapt teaching methods and integrate the tool productively into their courses.

Limitations and Future Research Directions

Despite providing informative evidence about the determinants of ChatGPT use behavior, this study is constrained by several limitations that warrant consideration when interpreting its findings. Primarily, the study's focus on higher education students within Nigeria raises concerns regarding the generalizability of its findings to other higher education students in other contexts. To address this limitation, future investigations could undertake comparative analyses across diverse cultural and educational settings. Furthermore, the reliance on self-reported data underscores the necessity for cautious interpretation of the results. Future research might benefit from employing mixed methods approaches, blending self-report surveys with observational or qualitative methodologies to validate and enrich the findings. Additionally, while the study incorporates an extended UTAUT framework, the existence of potentially unexplored variables influencing ChatGPT use warrants further investigation. Subsequent studies could explore additional factors such as individual variances, organizational contexts, or technological attributes to elucidate the adoption process comprehensively.

CONCLUSION

This study contributes to the literature on technology adoption in higher education, particularly on the use of ChatGPT among students in Nigeria. This research identified several key factors that directly and indirectly influence students' BIs and actual usage of ChatGPT. This study identified PE, SI, HM, and HB as significant positive predictors of students' BI to use ChatGPT. This finding suggested that students are more likely to adopt ChatGPT if they perceive it to be beneficial, if their peers or social networks influence them positively, derive pleasure or enjoyment from its use, and develop habitual usage patterns. Conversely, the study revealed that EE and FC are significant negative predictors of students' BI to use ChatGPT. This finding indicates that challenges related to ease of use and access to necessary resources may hinder students' willingness to adopt ChatGPT.

Regarding use behavior, the study identified FC, HM, HB, and BI as significant positive predictors, while PE and SI emerged as significant negative predictors. This finding suggested that, despite initial perceptions or social pressures, students may engage with ChatGPT based on their perceived ease of access, enjoyment, habitual tendencies, and intentions to use it. Moreover, the study reveals the mediating role of BI in linking various factors to students' ChatGPT usage behavior. While BI positively mediates the influence of PE, SI, HM, and HB on ChatGPT use behavior, it negatively mediates the effects of EE and FC. Thus, BI is an important mechanism through which different factors influence students' ChatGPT use behavior.

This study has several implications for educators, policymakers, and technology developers in higher education. First, the findings suggest that efforts should be directed toward enhancing students' perceptions of the benefits of using ChatGPT, addressing usability issues, and providing adequate support and resources to facilitate its adoption. Additionally, initiatives that promote a positive and enjoyable user experience, foster habitual usage patterns, and leverage social networks to encourage adoption can be beneficial. Furthermore, considering the significant mediating role of BI, interventions targeting students' intentions to use ChatGPT should be prioritized. This could involve educational campaigns, training programs, and incentives to promote a positive attitude toward ChatGPT and increase students' motivation to incorporate it into their academic workflows.

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