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# Structural Equation Modelling of ChatGPT Adoption: Testing a Modified UTAUT Model with Moderating Variables

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## Abstract

An extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model was followed in this study to examine factors associated with students' acceptance and use of ChatGPT in Nigerian higher education institutions. A cross-sectional correlational design was adopted, and the data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). Data were collected from 8,496 students in universities, polytechnics, colleges of education, and monotechnics using the 40-item Higher Education Students' ChatGPT Utilisation Questionnaire (HESCUQ), adapted from established scales. The instrument met the stated reliability (α and CR > 0.70) and validity criteria (AVE > 0.50; HTMT < 0.85). Behavioural intention was significantly associated with performance expectancy, hedonic motivation, and habit, while actual use behaviour was predicted by facilitating conditions, hedonic motivation, habit, and behavioural intention. Behavioural intention also mediated relationships between the predictors and use behaviour. Age, sex, and programme of study moderated several paths; enjoyment and habit had stronger effects among younger students, male students, and students in technology-oriented programmes. The findings have practical implications for educators, institutional leaders, and policymakers seeking to support the ethical and effective use of AI tools in teaching, learning, and curriculum design.

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## Practitioner Notes

1. Educators should discuss the academic uses and limitations of ChatGPT with students.
2. Government and institutional leaders should improve digital infrastructure to reduce barriers to use.
3. Peer-led activities can encourage student engagement with ChatGPT.
4. Assignments that incorporate ChatGPT responsibly may help students develop regular patterns of use.
5. Strengthening students' intention to use ChatGPT may encourage effective and sustained use.

## Keywords

Artificial intelligence, chatbots, ChatGPT, technology acceptance, structural equation modelling

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# Introduction

Artificial intelligence (AI) refers to technologies that enable machines to perform tasks that usually require human thinking, such as learning, decision-making and problem-solving (Omeh et al., 2026; Owan, 2026a). In education, AI is used in intelligent tutoring systems, learning management tools, automated grading programmes, chatbots and mobile learning applications (Owan et al., 2023). These applications can support teaching and learning through timely feedback, interactive communication and personalised learning activities.

ChatGPT is one of the AI tools increasingly used in education. As a large language model based on deep learning, it performs language-related tasks, including writing, translation and answering questions (Mohammed et al., 2025). It can generate human-like responses (Omeh et al., 2026), correct grammatical errors (Halaweh, 2023), support conversations (Rudolph et al., 2023), encourage critical thinking (Bitzenbauer, 2023), assist language learning (Jeon & Lee, 2023) and help prepare educational materials (Perkins et al., 2023). Other applications include classroom assessment (Owan, 2026b) and support for teaching activities (Mohammed et al., 2026; Samara & Kotsis, 2024). ChatGPT can also support creative learning activities by giving students immediate feedback (Hwang & Chen, 2023).

However, the use of ChatGPT raises concerns about academic dishonesty and plagiarism (Perkins, 2023), errors and algorithmic bias (Ray, 2023), and privacy, fairness and unequal access to paid versions (Rudolph et al., 2023). Excessive dependence on AI may also weaken creativity and reduce students' active engagement with ideas (Owan, 2026a). These concerns make it necessary to understand the factors that influence students' acceptance and use of the tool.

Previous studies have applied the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to examine students' willingness to use ChatGPT (Mohammed et al., 2026; Strzelecki, 2023). Research has also examined its educational applications and associated concerns. Isiaku et al. (2024) reported that ChatGPT can support continued technology use through feedback and assessment, while emphasising the need for clear ethical rules. Similarly, Adeshola and Adepoju (2024) found that ChatGPT can support writing, student engagement and teaching efficiency, although concerns about fairness, trust and academic honesty persist. Muhammad et al. (2025) also found that interactivity, motivation and instructional design were associated with student participation in technology-based learning environments, including the metaverse.

Although these studies contribute to our understanding of technology use in education, they do not fully establish how students' beliefs, motivations and demographic characteristics relate to both their intention to use ChatGPT and their actual use, particularly in African higher education. Moreover, little is known about how age, sex and programme of study influence the relationship between students' acceptance of ChatGPT, their intention to use it and their actual use of the tool in African universities. To address this gap, an extended UTAUT2 model was applied to examine factors associated with students' behavioural intention to use ChatGPT and their actual use of the tool. Specifically, the study assesses the relationships of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation and habit with behavioural intention and use behaviour. It also examines whether age, sex and programme of study moderate selected relationships. The study is intended to extend understanding of ChatGPT

adoption in a developing-country setting and inform efforts to promote its ethical and effective use in higher education.

## Literature

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), integrates eight earlier models of technology adoption: the Theory of Reasoned Action, Technology Acceptance Model, Motivational Model, Theory of Planned Behaviour, combined TAM–TPB framework, Model of PC Utilisation, Social Cognitive Theory and Innovation Diffusion Theory. UTAUT identifies performance expectancy, effort expectancy, social influence and facilitating conditions as factors associated with technology acceptance and use. Venkatesh et al. (2012) extended the model to UTAUT2 by adding hedonic motivation, price value and habit to explain consumer technology use. Age, gender and experience were included as moderating variables (Palau-Saumell et al., 2019).

In the present study, programme of study replaced experience to account for differences among students in higher education. Dwivedi et al. (2019) noted that previous studies often examined selected UTAUT2 constructs, with less attention to demographic moderators. Accordingly, age, sex and programme of study were included in the extended model. Age is relevant because younger users are generally more confident in adopting new technologies, whereas older users may face challenges associated with lower technological readiness or limited exposure (Schmitz et al., 2022; Venkatesh et al., 2012). Gender may also influence technology use, as male students have been reported to engage more actively with digital technologies and show greater interest in adoption than female students (Jaradat et al., 2020). Programme of study accounts for differences among students pursuing qualifications such as the Ordinary National Diploma (OND), Higher National Diploma (HND), Nigeria Certificate in Education (NCE) and university degrees from Bachelor's to Doctoral levels.

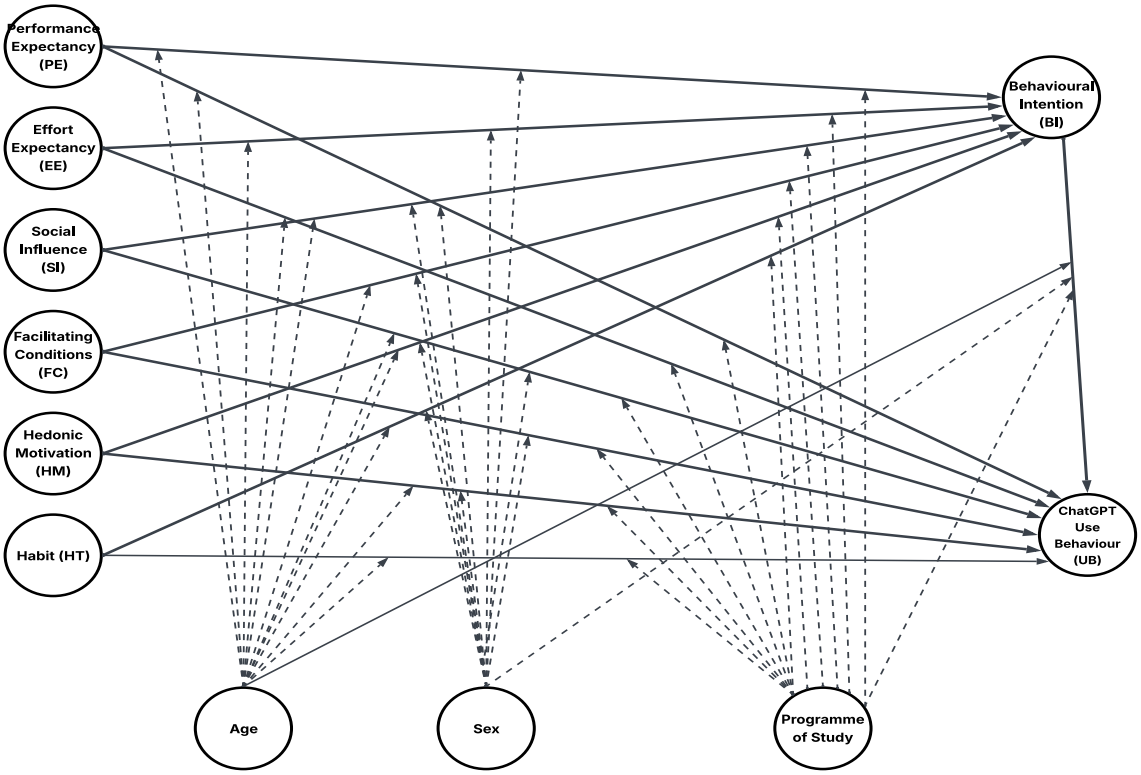
Under UTAUT2, performance expectancy and effort expectancy are positively associated with behavioural intention and technology use (Owan, Mohammed et al., 2025). Social influence and facilitating conditions may also support technology use, while hedonic motivation and habit encourage continued engagement. Habit develops through repeated interaction and is associated with continued use (Strzelecki, 2023). These relationships make UTAUT2 relevant to understanding students' adoption of ChatGPT.

As shown in Figure 1, the conceptual model includes six predictors: PE, EE, SI, FC, HM and HB. BI serves as the mediating variable, while ChatGPT use behaviour (UB) is the outcome. UB refers to the extent, frequency and nature of students' engagement with ChatGPT for academic tasks, including writing, problem-solving, learning support and information generation (Dwivedi et al., 2019).

Price value was excluded because most Nigerian students are understood to use the freely accessible version of ChatGPT. Previous research suggests that price value may have limited influence on BI when access is free or subsidised (Zhu et al., 2023). Age, sex and programme of study were therefore included as moderators to assess whether the relationships in the model differ across student groups (Udeozor et al., 2023). Related empirical studies are reviewed below according to the predictors in Figure 1.

**Figure 1**

*Conceptual Model of this Study Based on the Extended UTAUT Model.*




## Performance Expectancy

In this study, performance expectancy refers to students' perceptions of ChatGPT's usefulness for learning, research and other academic activities. Previous research has identified perceived usefulness as an important factor associated with behavioural intention (BI) to adopt technology (Schmitz et al., 2022). Studies in Nigerian universities have also linked PE to students' intention to use ChatGPT for academic purposes (Owan, Mohammed et al., 2025). Similarly, research has associated perceived usefulness with self-directed learning and students' patterns of ChatGPT use (Owan, Chukwu et al., 2025; Ofem et al., 2025). These findings suggest that students who consider ChatGPT useful may be more willing to use it for academic work.

Evidence concerning the moderating effects of age, gender and programme of study on the relationships between PE, BI and use behaviour (UB) remains mixed. Some studies have reported stronger PE effects among younger users (Jaradat et al., 2020), whereas Schmitz et al. (2022) found stronger effects among older individuals. Other studies have reported age moderation (Chang et al., 2019; Martins et al., 2018), while some found no significant effect (Nikolopoulou et al., 2021; Palau-Saumell et al., 2019). Gender-related findings are similarly inconsistent: some studies reported stronger PE effects among men (Jaradat et al., 2020; Puspitasari et al., 2019), while others found no significant moderation (Nikolopoulou et al., 2021; Palau-Saumell et al., 2019). Programme of study has also shown no significant moderating effect

(Human et al., 2020). These inconsistencies warrant further examination in Nigerian higher education.

> **Hypothesis 1:** Performance expectancy would have a significant influence on higher education students' behavioural intention to use ChatGPT and their actual use behaviour.
>
> **Hypothesis 2:** The effects of performance expectancy on higher education students' behavioural intention to use ChatGPT and their actual use behaviour would be moderated by age, gender, and programme of study.

### Effort Expectancy

Effort expectancy (EE) refers to the degree to which a technology is perceived as easy to learn and use (Xiaofan & Annamalai, 2025). Empirical research has linked EE with BI (Owan, Mohammed et al., 2025). However, evidence on demographic moderation is inconclusive. Some studies (Nikolopoulou et al., 2021) reported no significant age effect, whereas others (Chang et al., 2019; Martins et al., 2018) found stronger effects among older users. Findings on gender also vary, as some studies (Garg, 2021; Schmitz et al., 2022) reported stronger EE–BI relationships for women, while others (Chen et al., 2021; Palau-Saumell et al., 2019) found none. Findings on programme of study are also inconsistent (Human et al., 2020).

> **Hypothesis 3:** Effort expectancy would have a significant influence on higher education students' behavioural intention to use ChatGPT and their actual use behaviour.
>
> **Hypothesis 4:** The effects of effort expectancy on higher education students' behavioural intention to use ChatGPT and their actual use behaviour would be moderated by age, gender, and programme of study.

### Social Influence

Social influence (SI) refers to the extent to which individuals perceive that important people, such as peers and lecturers, expect them to use a technology (Venkatesh et al., 2012). In higher education, such expectations may influence students' behavioural intention (BI) and use behaviour (UB) (Schmitz et al., 2022). However, evidence on demographic moderation remains mixed. Some studies found that age moderated the SI relationship (Chen et al., 2021; Jaradat et al., 2020), while others found no significant effect (Nikolopoulou et al., 2021). Gender-related findings are similarly inconsistent, with some studies reporting stronger effects among women (Jaradat et al., 2020; Martins et al., 2018), while others found no significant differences (Chen et al., 2021; Schmitz et al., 2022). Evidence on programme of study remains inconclusive (Human et al., 2020).

> **Hypothesis 5:** Social influence would have a significant influence on higher education students' behavioural intention to use ChatGPT and their actual use behaviour.
>
> **Hypothesis 6:** The effects of social influence on higher education students' behavioural intention to use ChatGPT and their actual use behaviour would be moderated by age, gender, and programme of study.

### Facilitating Conditions

Facilitating conditions (FC) refer to the perceived availability of resources and support needed to use a technology (Owan, Mohammed et al., 2025; Strzelecki, 2023). These conditions may influence behavioural intention (BI) and use behaviour (UB) by affecting users' confidence in their access to technology and available support (Schmitz et al., 2022). Evidence on moderation by age and sex is mixed. Some studies reported stronger FC effects among older users (Martins et al., 2018), while others found no significant age effects (Palau-Saumell et al., 2019; Schmitz et al., 2022). Findings on sex also differ, and evidence on programme of study remains limited (Human et al., 2020).

> **Hypothesis 7.** Facilitating conditions would have a significant influence on higher education students' intention to use ChatGPT and their actual use behaviour.
>
> **Hypothesis 8.** The effect of facilitating conditions on higher education students' behavioural intentions to use ChatGPT would be moderated by age, gender, and programme of study.

### Hedonic Motivation

Hedonic motivation (HM) refers to the enjoyment or satisfaction associated with using a technology (Owan, Mohammed et al., 2025; Strzelecki, 2023). Evidence on demographic moderation is mixed. Some studies reported stronger HM effects among younger users (Garg, 2021; Schmitz et al., 2022), whereas others found no significant age effect (Nikolopoulou et al., 2021). Findings on sex also vary with some studies reporting that men responded more strongly to hedonic value (Chang et al., 2019; Martins et al., 2018), while others found no difference (Garg, 2021; Nikolopoulou et al., 2021). The moderating role of programme of study has received limited attention (Human et al., 2020).

> **Hypothesis 9:** Hedonic motivation would have a significant influence on higher education students' behavioural intention to use ChatGPT and their actual use behaviour.
>
> **Hypothesis 10:** The effects of hedonic motivation on higher education students' behavioural intention to use ChatGPT and their actual use behaviour would be moderated by age, gender, and programme of study.

### Habit

Habit refers to behaviour that becomes automatic through repeated use of a technology (Owan, Mohammed et al., 2025). Once students become accustomed to ChatGPT, they may use it with little conscious effort (Strzelecki, 2023; Venkatesh et al., 2012). Evidence on demographic moderation is mixed. Some studies reported age effects (Chang et al., 2019; Martins et al., 2018), while others found none (Nikolopoulou et al., 2021; Palau-Saumell et al., 2019; Schmitz et al., 2022). Findings on sex and programme of study are similarly inconsistent (Human et al., 2020).

> **Hypothesis 11:** Habit would have a significant influence on higher education students' behavioural intention to use ChatGPT and their actual use behaviour.
>
> **Hypothesis 12:** The effects of habit on higher education students' behavioural intention to use ChatGPT and their actual use behaviour would be moderated by age, gender, and programme of study.

### Behavioural Intention

Behavioural intention (BI) refers to a person's willingness to use a technology (Owan, Mohammed et al., 2025). In this study, BI concerns students' intention to use ChatGPT for academic purposes. It mediates the relationship between UTAUT2 constructs (PE, EE, SI, FC, HM, HT) and actual use behaviour (UB) (Huang, 2023). Previous research (Petters et al., 2024) identifies BI as a strong predictor of actual use, although most of these studies were conducted outside Nigeria.

> **Hypothesis 13:** BI would have a significant influence on higher education students' ChatGPT use behaviour (UB), after controlling for age, gender, and programme of study.
>
> **Hypothesis 14:** BI would significantly mediate the relationships of PE, EE, SI, FC, HM, and HT with UB, after controlling for age, gender, and programme of study.

## Method

A cross-sectional correlational design was adopted to examine factors associated with students' use of ChatGPT in selected higher education institutions in Nigeria. The study was based on the Unified Theory of Acceptance and Use of Technology (UTAUT2), with six predictors: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation and habit. These variables were examined in relation to behavioural intention and use behaviour, while age, sex and programme of study were included as moderating variables.

### Participants

Participants were undergraduate and postgraduate students from Nigerian universities, polytechnics, colleges of education and monotechnics. Data were collected between October 2023 and February 2024 through an online questionnaire distributed via institutional mailing lists, student forums and Telegram channels. Class representatives and faculty-managed platforms helped coordinate participation. Duplicate and invalid responses were minimised by restricting submissions to one per device or email address and requiring confirmation of institutional affiliation. Participation was voluntary, with no financial incentives.

Of the 9,000 invitations sent, 8,496 responses were received. After incomplete, inconsistent and duplicate entries were removed, 8,472 valid responses remained, representing a response rate of 94.1%. Convenience sampling was used. The sample size supported PLS-SEM estimation and bootstrapping (Hair et al., 2021), as well as subgroup analyses (Ringle et al., 2012).

Most participants were aged 18–34 years, although a small proportion were below 18 and classified as early-entry undergraduates. Ethical approval was obtained. A waiver of written consent covered minors, whose assent was implied by voluntary questionnaire completion after receiving information about the study, confidentiality and their right to withdraw.

### Instrument and Measures

Data were collected using the Higher Education Students' ChatGPT Utilisation Questionnaire (HESCUQ), administered through Google Forms. The instrument comprised three sections. The first explained the study's purpose and sought informed consent; email addresses were collected only to verify unique responses. The second collected demographic information, including age, sex and programme of study. The third measured the UTAUT2 constructs using items adapted

from validated studies. Responses were rated on a four-point Likert scale, from 1 (strongly disagree) to 4 (strongly agree).

Performance expectancy (PE) comprised five items adapted from Bin-Nashwan et al. (2023) and Shahsavar and Choudhury (2023), assessing perceived academic usefulness, including content generation. Effort expectancy (EE) comprised five items from Ma and Huo (2023), measuring ease of use and interaction. Social influence (SI) was measured with five items from Strzelecki (2023), covering the influence of peers and lecturers. Facilitating conditions (FC) comprised five items from Strzelecki (2023), assessing access to resources and support. Hedonic motivation (HM) comprised five items from Habibi et al. (2023), measuring enjoyment of use. Habit (HB) was measured with five items from Owan, Mohammed et al. (2025), assessing automaticity of use.

Behavioural intention (BI) comprised five items adapted from Ma and Huo (2023) and Shahsavar and Choudhury (2023), assessing intentions to continue using ChatGPT. Use behaviour (UB) comprised six items from Strzelecki (2023), measuring the frequency and consistency of use, including idea generation and routine reliance. The final instrument contained 40 items covering the eight UTAUT2 constructs and adapted to AI use in higher education.

### Validity and Reliability

Content validity was assessed by three psychometrists and four educational technologists. The item-level CVI ranged from .74 to .99, while the scale-level CVI exceeded .90. Items were revised based on their feedback, and a pilot test involving 15 students confirmed their clarity.

EFA was conducted in SPSS version 27 using principal axis factoring and Promax rotation. Eight factors were obtained, consistent with the theoretical model. The KMO value was .93, and Bartlett's test of sphericity was significant ($p < .001$). Items with factor loadings below .50 were removed. Reliability was assessed using Cronbach's alpha and CR, with values above .70 meeting the recommended thresholds. AVE values exceeded .50, supporting convergent validity. Discriminant validity was assessed using the Fornell–Larcker criterion and HTMT. Common method bias was addressed through anonymity, item randomisation and separation of predictor and outcome sections.

A separate CFA was not conducted because PLS-SEM uses a variance-based composite approach. Measurement quality was assessed through indicator reliability, internal consistency, convergent validity and discriminant validity, following Hair et al. (2021). Global fit indices were not required, as emphasis was placed on measurement quality and predictive relevance (Becker et al., 2023).

### Data Analysis

Data were analysed using SmartPLS 4.0 in two stages: assessment of the measurement model and evaluation of the structural model. The measurement model was assessed in terms of indicator loadings, internal consistency reliability and validity. The structural model was evaluated using path coefficients, t-values and p-values to determine the significance of the hypothesised relationships. Model performance was assessed using the coefficient of determination ($R^2$), predictive relevance ($Q^2$) and effect size ($f^2$). Moderation was tested by creating interaction terms between age, sex and programme of study and selected predictors. These interaction terms were included in the model to determine whether the strength or direction of the relationships differed

across the demographic groups. The significance of the interaction effects was assessed through bootstrapping.

### Ethical Considerations and Data Collection Procedure

Data were collected between October 2023 and February 2024, before the University of Calabar Research Ethics Committee commenced operations. Ethical matters were handled through existing institutional arrangements during this period. Following the Committee's establishment, retrospective institutional review was conducted, and approval was granted on 23 September 2024 (UNICAL/REC/2024/039), after data collection had ended.

Participation was voluntary. Participants received information about the study, confidentiality and their right to withdraw before completing the online questionnaire. Consent was obtained through the questionnaire's introductory procedure. Email addresses were collected solely to prevent duplicate submissions and were not linked to individual responses during analysis. Data were stored on a password-protected computer.

## Results

The results are presented in three parts. Part A reports the measurement model assessment, including the reliability and validity of the constructs. Part B presents the structural model and tests the relationships among the main variables, including the mediation effect of behavioural intention (BI). Part C reports the moderation analysis and considers whether age, sex, and programme of study affect these relationships.

### Part A: Measurement Model and Quality Criteria Assessment

The measurement model was assessed using indicator loadings, VIF, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE) and descriptive statistics, as shown in Table 1. All item loadings exceeded 0.70, while VIF values ranged from 1.23 to 2.94, indicating no serious multicollinearity. Cronbach's alpha ranged from 0.664 to 0.895, while CR ranged from 0.811 to 0.923. Although all CR values exceeded 0.70, the lowest alpha was slightly below this threshold. AVE values ranged from 0.589 to 0.705, meeting the 0.50 criterion for convergent validity. Skewness and kurtosis were mostly within ±2. Overall, the measurement model was satisfactory, although the lowest alpha value warrants caution.

**Table 1**

*Measurement Model Results for Reliability and Convergent Validity*

| Construct | Items | M | SD | Skew. | Kurt. | λ | VIF | α | CR | AVE |
|---|---|---|---|---|---|---|---|---|---|---|
| **Effort expectancy (EE)** | EE1 | 3.14 | 0.73 | -0.93 | 1.41 | 0.75 | 1.69 | 0.788 | 0.860 | 0.607 |
| | EE2 | 3.06 | 0.71 | -0.62 | 0.67 | 0.81 | 1.74 | | | |
| | EE4 | 3.19 | 0.64 | -0.83 | 2.07 | 0.75 | 1.55 | | | |
| | EE5 | 3.06 | 0.64 | -0.52 | 1.09 | 0.81 | 1.48 | | | |
| **Facilitating Conditions (FC)** | FC1 | 2.87 | 0.74 | -0.29 | -0.14 | 0.81 | 1.74 | 0.804 | 0.872 | 0.630 |
| | FC2 | 2.77 | 0.77 | -0.28 | -0.24 | 0.82 | 1.90 | | | |
| | FC3 | 2.98 | 0.72 | -0.47 | 0.30 | 0.82 | 1.66 | | | |
| | FC4 | 2.95 | 0.72 | -0.51 | 0.38 | 0.72 | 1.49 | | | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Habit (HB)** | HB1 | 2.60 | 0.86 | -0.19 | -0.58 | 0.80 | 2.00 | 0.895 | 0.923 | 0.705 |
| | HB2 | 2.58 | 0.83 | 0.02 | -0.59 | 0.89 | 2.94 | | | |
| | HB3 | 2.55 | 0.84 | -0.01 | -0.60 | 0.88 | 2.79 | | | |
| | HB4 | 2.40 | 0.86 | 0.07 | -0.64 | 0.82 | 2.24 | | | |
| | HB5 | 2.50 | 0.83 | -0.13 | -0.56 | 0.82 | 2.13 | | | |
| **Hedonic** | HM1 | 3.06 | 0.65 | -0.61 | 1.21 | 0.80 | 1.95 | 0.859 | 0.898 | 0.639 |
| **Motivation** | HM2 | 3.02 | 0.67 | -0.53 | 0.83 | 0.76 | 1.66 | | | |
| **(HM)** | HM3 | 3.03 | 0.65 | -0.64 | 1.31 | 0.79 | 1.86 | | | |
| | HM4 | 2.95 | 0.71 | -0.71 | 0.99 | 0.80 | 1.73 | | | |
| | HM5 | 3.00 | 0.70 | -0.74 | 1.14 | 0.85 | 2.26 | | | |
| **Performance** | PE1 | 3.21 | 0.71 | -1.18 | 2.41 | 0.76 | 1.76 | 0.847 | 0.891 | 0.621 |
| **Expectancy** | PE2 | 3.15 | 0.71 | -1.04 | 1.98 | 0.79 | 1.82 | | | |
| **(PE)** | PE3 | 3.19 | 0.70 | -0.87 | 1.37 | 0.75 | 1.58 | | | |
| | PE4 | 3.10 | 0.68 | -0.77 | 1.40 | 0.82 | 1.93 | | | |
| | PE5 | 3.09 | 0.69 | -0.79 | 1.37 | 0.82 | 1.90 | | | |
| **Social** | SI2 | 2.86 | 0.73 | -0.48 | 0.28 | 0.82 | 1.24 | 0.664 | 0.811 | 0.589 |
| **Influence (SI)** | SI3 | 2.42 | 0.84 | 0.19 | -0.55 | 0.75 | 1.31 | | | |
| | SI4 | 2.66 | 0.80 | -0.25 | -0.36 | 0.72 | 1.37 | | | |
| **Behavioural** | BI1 | 2.95 | 0.68 | -0.66 | 1.11 | 0.73 | 1.58 | 0.855 | 0.896 | 0.633 |
| **Intention (BI)** | BI2 | 2.78 | 0.77 | -0.31 | -0.19 | 0.82 | 1.98 | | | |
| | BI3 | 3.04 | 0.69 | -0.62 | 0.91 | 0.78 | 1.79 | | | |
| | BI4 | 2.80 | 0.79 | -0.34 | -0.23 | 0.84 | 2.12 | | | |
| | BI5 | 3.02 | 0.65 | -0.59 | 1.22 | 0.81 | 1.86 | | | |
| **ChatGPT Use** | UB3 | 2.95 | 0.70 | -0.61 | 0.79 | 0.79 | 1.63 | 0.829 | 0.886 | 0.661 |
| **Behaviour** | UB4 | 3.03 | 0.65 | -0.76 | 1.70 | 0.78 | 1.69 | | | |
| **(UB)** | UB5 | 2.83 | 0.72 | -0.24 | -0.12 | 0.85 | 2.11 | | | |
| | UB6 | 2.76 | 0.81 | -0.29 | -0.38 | 0.83 | 1.83 | | | |

Note. λ = standardized factor loading; VIF = variance inflation factor; α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

### *Multivariate Distribution Assessment*

Multivariate normality and outliers were examined. Mardia's coefficients were used to assess multivariate skewness and kurtosis. The reported values were multivariate skewness = 32.14, p = .12, and multivariate kurtosis = 45.67, p = .09, suggesting no extreme departure from multivariate normality (Mardia, 1970). Mahalanobis distances were used to identify multivariate outliers. No cases exceeded the critical $\chi^2$ value at $p < .001$, indicating that no extreme multivariate outliers were detected (Mahalanobis, 1936).

### *Discriminant validity*

Discriminant validity was assessed using the Fornell–Larcker criterion and the HTMT ratio. As shown in Table 3, the square roots of AVE exceeded the inter-construct correlations, satisfying the Fornell–Larcker criterion (Fornell & Larcker, 1981). All HTMT values were below 0.85, providing further evidence of discriminant validity (Henseler et al., 2015).

**Table 2**

*Fornell-Larcker Criterion for Discriminant Validity*

| | EE | FC | HB | HM | PE | SI | BI | UB |
|---|---|---|---|---|---|---|---|---|
| **EE** | **0.779** | | | | | | | |
| **FC** | 0.566 | **0.794** | | | | | | |
| **HB** | 0.375 | 0.436 | **0.840** | | | | | |
| **HM** | 0.555 | 0.611 | 0.54 | **0.799** | | | | |
| **PE** | 0.609 | 0.49 | 0.37 | 0.63 | **0.788** | | | |
| **SI** | 0.282 | 0.285 | 0.427 | 0.383 | 0.216 | **0.768** | | |
| **BI** | 0.345 | 0.367 | 0.599 | 0.577 | 0.428 | 0.323 | **0.795** | |
| **UB** | 0.397 | 0.502 | 0.628 | 0.621 | 0.41 | 0.315 | 0.662 | **0.813** |

**Note.** Diagonal elements (bolded) are the square roots of the AVEs.

**Table 3**

*Heterotrait–Monotrait (HTMT) Ratio of Correlations*

| | EE | FC | HB | HM | PE | SI | BI | UB |
|---|---|---|---|---|---|---|---|---|
| **EE** | — | | | | | | | |
| **FC** | 0.700 | — | | | | | | |
| **HB** | 0.424 | 0.508 | — | | | | | |
| **HM** | 0.675 | 0.731 | 0.605 | — | | | | |
| **PE** | 0.750 | 0.585 | 0.417 | 0.734 | — | | | |
| **SI** | 0.362 | 0.378 | 0.561 | 0.473 | 0.261 | — | | |
| **BI** | 0.405 | 0.434 | 0.671 | 0.663 | 0.500 | 0.393 | — | |
| **UB** | 0.476 | 0.604 | 0.717 | 0.731 | 0.488 | 0.409 | 0.780 | — |

**Note.** All HTMT values are below the 0.85 threshold, indicating satisfactory discriminant validity

***Predictive Validity***

Predictive validity was assessed using PLS-Predict and the Cross-Validated Predictive Ability Test (CVPAT). As shown in Table 4, all indicators had positive $Q^2$predict values, ranging from 0.192 to 0.440, indicating out-of-sample predictive relevance (Shmueli et al., 2019). However, the PLS-SEM RMSE values were higher than those of the LM for all indicators, although they were lower than those of the IA benchmark. The construct-level CVPAT results in Table 5 show that PLS-SEM performed better than IA for both BI and UB but slightly less well than LM. The indicator-level CVPAT results in Table 6 confirm this pattern: PLS-SEM had lower prediction losses than IA but higher losses than LM across all indicators. Thus, the model showed predictive relevance, although its predictive performance was slightly lower than that of the LM.

**Table 4**

*PLS-Predict Results Showing Indicator-Level Predictive Validity*

| Indicator | $Q^2$predict | PLS-SEM RMSE | LM RMSE | IA RMSE |
|---|---|---|---|---|
| **BI1** | 0.206 | 0.601 | 0.560 | 0.675 |
| **BI2** | 0.331 | 0.630 | 0.599 | 0.771 |
| **BI3** | 0.192 | 0.618 | 0.587 | 0.688 |

| | | | | |
|---|---|---|---|---|
| **BI4** | 0.385 | 0.620 | 0.576 | 0.791 |
| **BI5** | 0.313 | 0.536 | 0.518 | 0.646 |
| **UB3** | 0.329 | 0.574 | 0.554 | 0.701 |
| **UB4** | 0.276 | 0.557 | 0.532 | 0.654 |
| **UB5** | 0.304 | 0.600 | 0.573 | 0.719 |
| **UB6** | 0.440 | 0.609 | 0.567 | 0.814 |

**Note.** $Q^2$predict > 0 indicates predictive relevance. Positive $Q^2$predict values indicate out-of-sample predictive relevance. Lower RMSE values indicate greater predictive accuracy when comparing models.

**Table 5**

*Construct-Level CVPAT Comparing PLS-SEM with Benchmark Models*

| Comparison | Construct | PLS Loss | Benchmark Loss | Avg. Loss Difference | t | p |
|---|---|---|---|---|---|---|
| **PLS-SEM vs IA** | BI | 0.363 | 0.513 | −0.151 | 27.256 | 0.000 |
| | UB | 0.343 | 0.525 | −0.182 | 32.158 | 0.000 |
| | Overall | 0.354 | 0.518 | −0.165 | 32.03 | 0.000 |
| **PLS-SEM vs LM** | BI | 0.363 | 0.323 | 0.039 | 23.2 | 0.000 |
| | UB | 0.343 | 0.310 | 0.033 | 20.995 | 0.000 |
| | Overall | 0.354 | 0.317 | 0.036 | 30.723 | 0.000 |

**Note.** Negative average loss differences indicate superior predictive ability of PLS-SEM.

**Table 6**

*Indicator-Level CVPAT Comparing PLS-SEM with Benchmark Models*

| Comparison | Indicator | PLS Loss | Benchmark Loss | Avg. Loss Difference | t | p |
|---|---|---|---|---|---|---|
| **PLS-SEM vs IA** | BI1 | 0.362 | 0.455 | −0.094 | 16.693 | 0.000 |
| | BI2 | 0.397 | 0.594 | −0.197 | 25.714 | 0.000 |
| | BI3 | 0.382 | 0.473 | −0.091 | 13.611 | 0.000 |
| | BI4 | 0.385 | 0.625 | −0.241 | 31.783 | 0.000 |
| | BI5 | 0.287 | 0.418 | −0.131 | 22.46 | 0.000 |
| | UB3 | 0.330 | 0.492 | −0.162 | 23.243 | 0.000 |
| | UB4 | 0.310 | 0.428 | −0.118 | 18.485 | 0.000 |
| | UB5 | 0.360 | 0.518 | −0.157 | 21.500 | 0.000 |
| | UB6 | 0.371 | 0.663 | −0.292 | 37.067 | 0.000 |
| **PLS-SEM vs LM** | BI1 | 0.362 | 0.314 | 0.047 | 14.713 | 0.000 |
| | BI2 | 0.397 | 0.359 | 0.039 | 13.236 | 0.000 |
| | BI3 | 0.382 | 0.345 | 0.037 | 11.540 | 0.000 |
| | BI4 | 0.385 | 0.331 | 0.053 | 14.884 | 0.000 |
| | BI5 | 0.287 | 0.268 | 0.019 | 10.105 | 0.000 |
| | UB3 | 0.330 | 0.307 | 0.023 | 9.897 | 0.000 |
| | UB4 | 0.310 | 0.283 | 0.027 | 11.546 | 0.000 |
| | UB5 | 0.360 | 0.329 | 0.031 | 10.400 | 0.000 |
| | UB6 | 0.371 | 0.321 | 0.050 | 16.219 | 0.000 |

The density plots and normal histograms for BI (Figure 2) and UB (Figure 3) indicate that the residuals were approximately normally distributed around zero. In both cases, the histogram bars followed the normal curve reasonably well. The BI distribution was concentrated around the mean, suggesting relatively small and consistent prediction errors. Similarly, the UB distribution was approximately symmetrical, with no substantial deviations or outliers. These patterns are consistent with the residual distribution described above.

**Figure 2**

*Density and Normal Histogram of Behavioural Intention (BI) Residuals.*

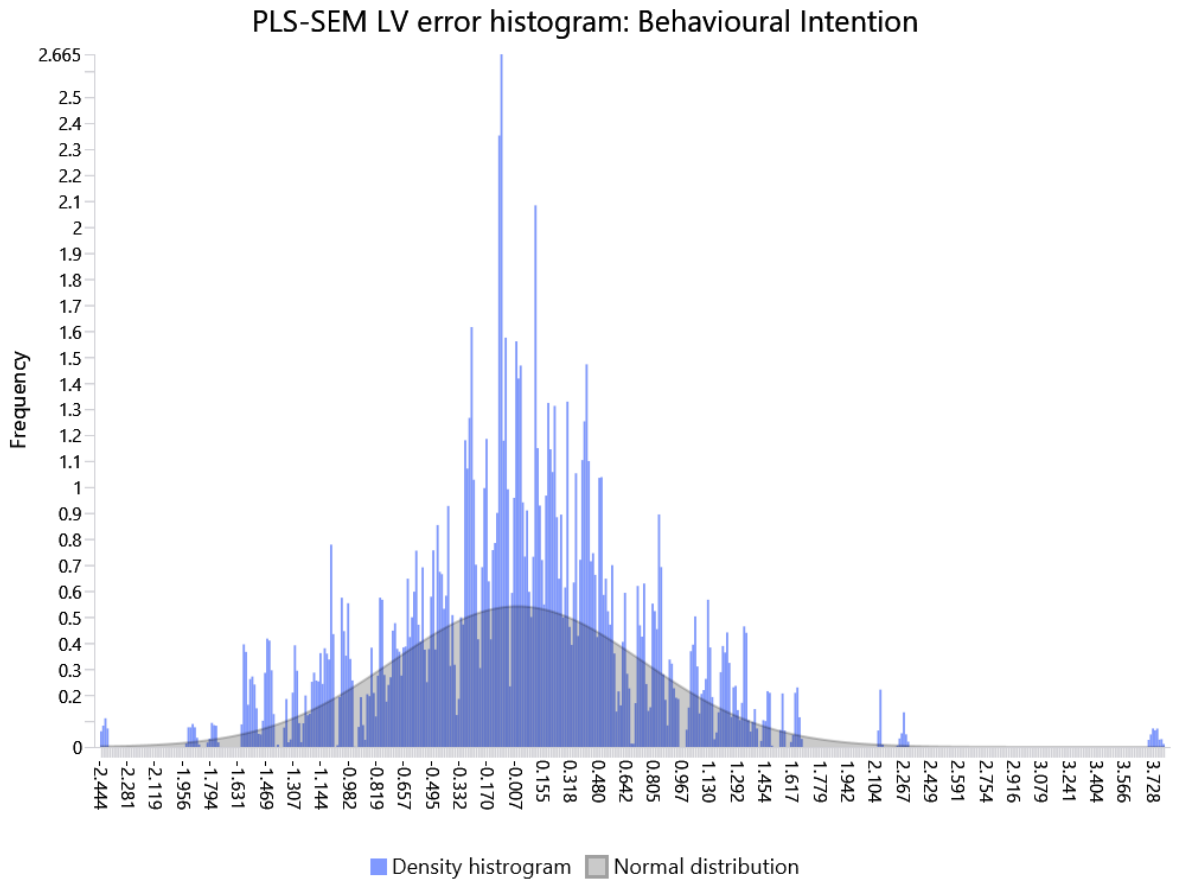
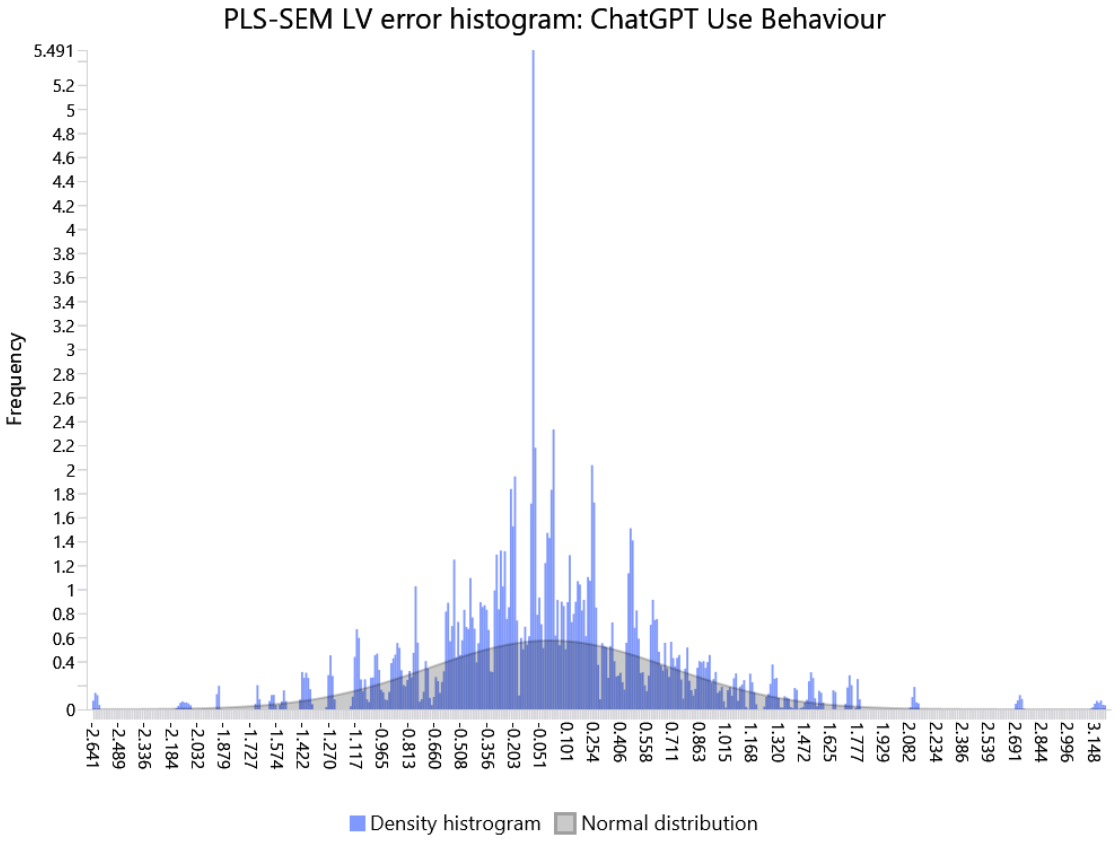


**Figure 3**

*Density and Normal Histogram of Use Behaviour (UB) Residuals.*




## Part B: Structural Model and Hypothesis Testing

This section reports the relationships between the variables and tests the hypotheses derived from UTAUT2 and the conceptual model in Figure 4. The results are presented under direct effects (Table 7) and mediation effects (Table 8).

### *Direct Effects*

As presented in Figure 4 and Table 7, most hypotheses were supported. Performance expectancy (PE) was positively related to behavioural intention (BI) but negatively related to use behaviour (UB), supporting H1, although both effects were negligible. Effort expectancy (EE) was negatively related to BI, supporting H2A, but had no significant relationship with UB; thus, H2B was not supported. Social influence (SI) was positively related to BI but negatively related to UB, supporting H3. Facilitating conditions (FC) were negatively related to BI and positively related to UB, supporting H4. Hedonic motivation had positive relationships with BI and UB, supporting H5A and H5B, with small effects. Habit positively predicted both outcomes, supporting H6A and H6B, with medium and small effects, respectively. BI positively predicted UB, supporting H7, with a medium effect.

**Figure 4**

*Structural Model of the Study*

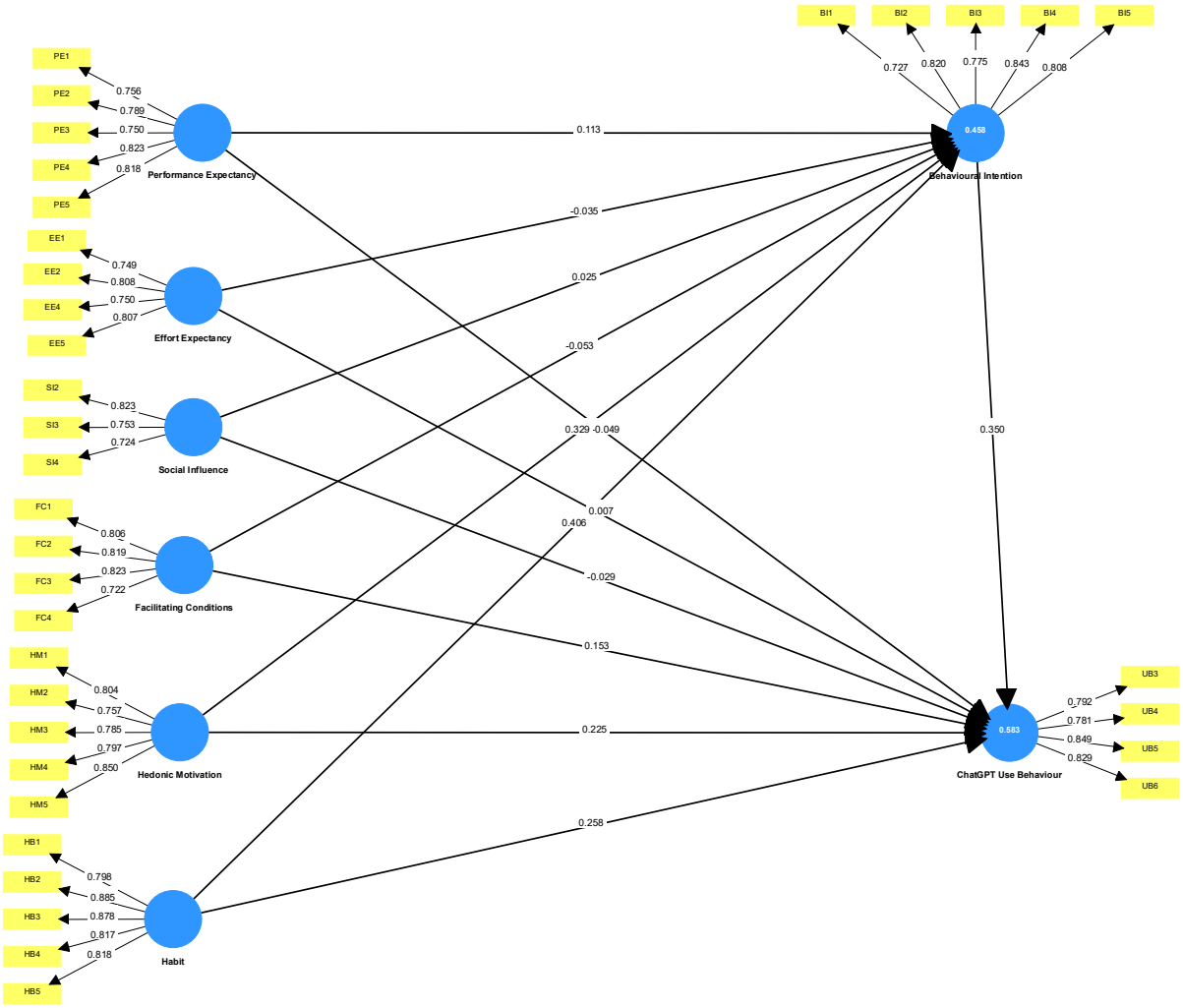



**Table 7**

*Results of Structural Model Path Coefficients*

| Hypotheses | β | SD | t | *p* | f² | Remark |
|---|---|---|---|---|---|---|
| **H1A: PE → BI** | 0.113 | 0.012 | 9.596 | 0.000 | 0.012 | Supported |
| **H1B: PE → UB** | −0.049 | 0.011 | 4.446 | 0.000 | 0.003 | Supported |
| **H2A: EE → BI** | −0.035 | 0.014 | 2.500 | 0.012 | 0.001 | Supported |
| **H2B: EE → UB** | 0.007 | 0.012 | 0.567 | 0.571 | 0.000 | Not supported |
| **H3A: SI → BI** | 0.025 | 0.011 | 2.312 | 0.021 | 0.001 | Supported |
| **H3B: SI → UB** | −0.029 | 0.009 | 3.148 | 0.002 | 0.002 | Supported |
| **H4A: FC → BI** | −0.053 | 0.015 | 3.594 | 0.000 | 0.003 | Supported |
| **H4B: FC → UB** | 0.153 | 0.012 | 12.626 | 0.000 | 0.030 | Supported |
| **H5A: HM → BI** | 0.329 | 0.016 | 20.150 | 0.000 | 0.082 | Supported |
| **H5B: HM → UB** | 0.225 | 0.013 | 16.726 | 0.000 | 0.046 | Supported |

| | | | | | | |
|---|---|---|---|---|---|---|
| **H6A: HT → BI** | 0.406 | 0.011 | 36.415 | 0.000 | 0.193 | Supported |
| **H6B: HT → UB** | 0.258 | 0.013 | 19.560 | 0.000 | 0.085 | Supported |
| **H7: BI → UB** | 0.350 | 0.013 | 26.095 | 0.000 | 0.160 | Supported |

***Behavioural Intention as a Mediator***

The results in Table 7 shows that BI fully mediated the relationship between Effort Expectancy and Use Behaviour because the indirect effect was significant, whereas the direct effect was not. Hedonic Motivation and Habit had partial mediation, with significant direct and indirect effects in the same direction. In contrast, PE, SI and FC had inconsistent mediation because their significant direct and indirect effects were in opposite directions.

**Table 8**

*Indirect Relationships of Exogenous Constructs on ChatGPT Use Behaviour via Behavioural Intention*

| Hypotheses | β | SD | t | *p* | Remark |
|---|---|---|---|---|---|
| **H8A: PE → BI → UB** | 0.039 | 0.004 | 9.139 | 0.000 | Supported |
| **H8B: EE → BI → UB** | -0.012 | 0.005 | 2.534 | 0.011 | Supported |
| **H8C: SI → BI → UB** | 0.009 | 0.004 | 2.272 | 0.023 | Supported |
| **H8D: FC → BI → UB** | -0.018 | 0.005 | 3.485 | 0.000 | Supported |
| **H8E: HM → BI → UB** | 0.115 | 0.006 | 17.868 | 0.000 | Supported |
| **H8F: HT → BI → UB** | 0.142 | 0.007 | 20.783 | 0.000 | Supported |

**Part C: Demographic Variables as Moderators**

After controlling for age, sex and programme of study, the moderation results are presented in Table 9 and Figure 5. PE, HM and Habit were significant predictors of BI, while HM, Habit and BI were significant predictors of UB. Age and sex were positively related to BI but negatively related to UB, whereas programme of study was negatively related to BI and positively related to UB.

Age moderated the relationships of PE, EE, FC, HM and Habit with BI. The negative interactions for PE, HM and Habit indicate weaker relationships with BI among older students, while the positive interactions for EE and FC indicate stronger relationships. Age also moderated the relationships of PE, EE and BI with UB. The negative interaction involving BI suggests that the relationship between intention and actual use was weaker among older students.

Sex moderated the relationships of PE, SI, FC and Habit with BI. It also moderated the relationships of EE, SI, HM and BI with UB. These interactions indicate that the relationships between the predictors and the outcomes differed between male and female students. However, the direction of these differences depends on how sex was coded in the model.

Programme of study moderated the relationships of PE, EE, SI, FC and Habit with BI. It also moderated the relationships of PE, EE, SI and BI with UB. These results indicate that the relationships between the acceptance factors and BI, as well as between the predictors and UB, differed across programmes of study. The positive interaction between programme of study and BI indicates that the relationship between intention and actual use became stronger as the

programme variable increased. The precise interpretation depends on how programme of study was coded. The full moderation results are reported in Table 9 and Figure 5.

**Figure 5**

*Structural Model of the Study Moderated by Demographic Variables*

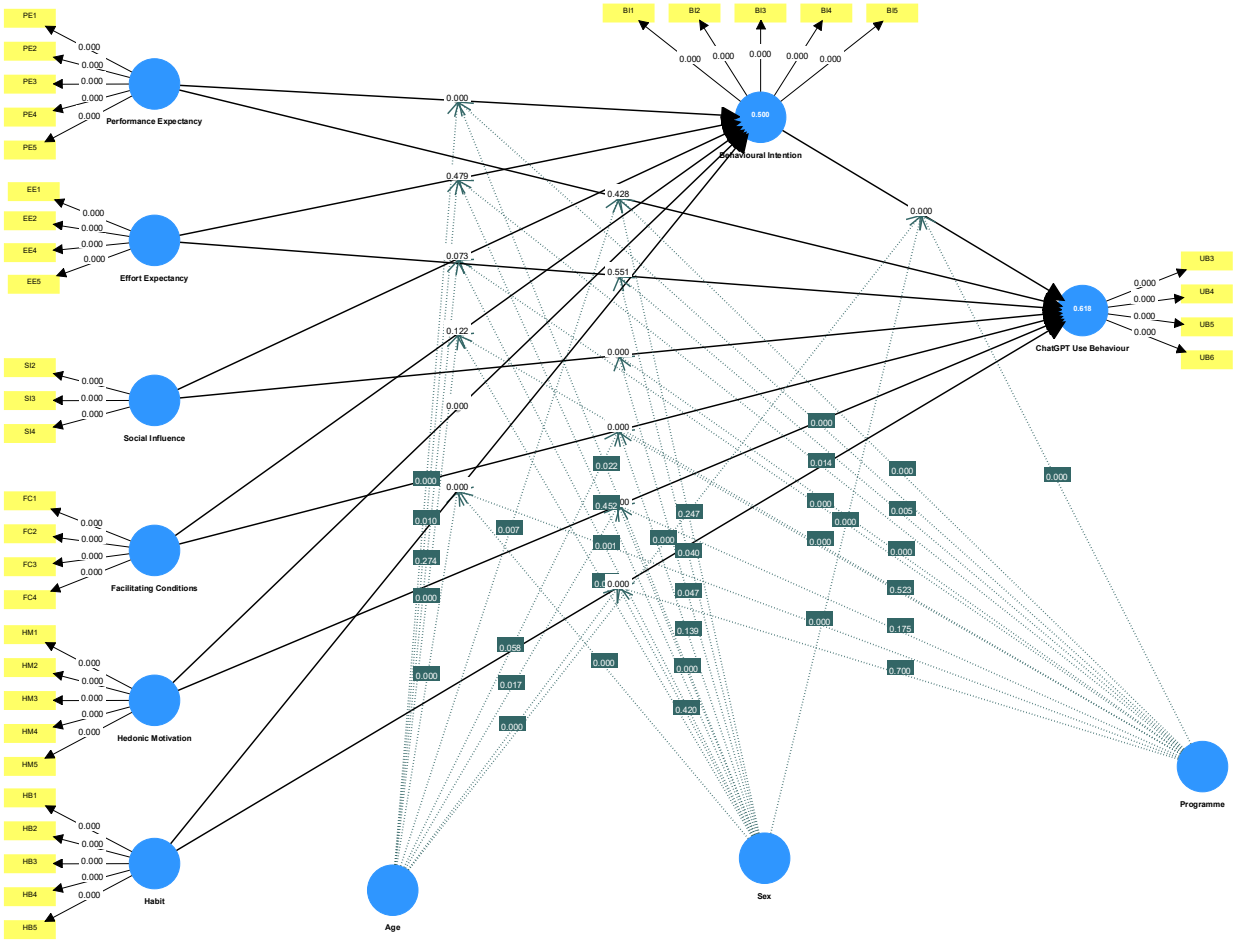



**Table 9**

*Moderated structural path coefficients for behavioural intention and ChatGPT use behaviour*

| Paths | β | *SD* | *t* | *p* | *Remark* |
|---|---|---|---|---|---|
| **PE → BI** | 0.106 | 0.016 | 6.616 | 0.000 | Significant |
| **PE → UB** | -0.011 | 0.014 | 0.793 | 0.428 | Not significant |
| **EE → BI** | -0.011 | 0.016 | 0.708 | 0.479 | Not significant |
| **EE → UB** | 0.009 | 0.016 | 0.596 | 0.551 | Not significant |
| **SI → BI** | -0.021 | 0.012 | 1.793 | 0.073 | Not significant |
| **SI → UB** | -0.046 | 0.011 | 4.180 | 0.000 | Significant |
| **FC → BI** | 0.027 | 0.017 | 1.547 | 0.122 | Not significant |
| **FC → UB** | 0.134 | 0.017 | 8.081 | 0.000 | Significant |

| | | | | | |
|---|---|---|---|---|---|
| **HM → BI** | 0.313 | 0.015 | 20.337 | 0.000 | Significant |
| **HM → UB** | 0.265 | 0.015 | 17.563 | 0.000 | Significant |
| **HT → BI** | 0.446 | 0.013 | 33.946 | 0.000 | Significant |
| **HT → UB** | 0.262 | 0.016 | 16.840 | 0.000 | Significant |
| **BI → UB** | 0.292 | 0.015 | 19.558 | 0.000 | Significant |
| **Age → BI** | 0.040 | 0.011 | 3.736 | 0.000 | Significant |
| **Age → UB** | -0.057 | 0.009 | 6.333 | 0.000 | Significant |
| **Sex → BI** | 0.080 | 0.017 | 4.811 | 0.000 | Significant |
| **Sex → UB** | -0.065 | 0.015 | 4.260 | 0.000 | Significant |
| **Programme → BI** | -0.075 | 0.011 | 6.582 | 0.000 | Significant |
| **Programme → UB** | 0.055 | 0.010 | 5.756 | 0.000 | Significant |
| **Age x PE → BI** | -0.125 | 0.018 | 7.084 | 0.000 | Significant |
| **Age x PE → UB** | 0.035 | 0.013 | 2.716 | 0.007 | Significant |
| **Age x EE → BI** | 0.043 | 0.017 | 2.587 | 0.010 | Significant |
| **Age x SI → BI** | -0.011 | 0.010 | 1.094 | 0.274 | Not significant |
| **Age x FC → BI** | 0.146 | 0.021 | 6.881 | 0.000 | Significant |
| **Age x FC → UB** | -0.033 | 0.017 | 1.894 | 0.058 | Not significant |
| **Age x HM → BI** | -0.071 | 0.016 | 4.391 | 0.000 | Significant |
| **Age x HM → UB** | 0.042 | 0.018 | 2.381 | 0.017 | Significant |
| **Age x HT → BI** | -0.119 | 0.014 | 8.682 | 0.000 | Significant |
| **Age x HT → UB** | 0.106 | 0.014 | 7.587 | 0.000 | Significant |
| **Age x BI → UB** | -0.167 | 0.017 | 9.767 | 0.000 | Significant |
| **Sex x PE → BI** | -0.060 | 0.026 | 2.298 | 0.022 | Significant |
| **Sex x PE → UB** | -0.022 | 0.019 | 1.157 | 0.247 | Not significant |
| **Sex x EE → BI** | 0.020 | 0.027 | 0.752 | 0.452 | Not significant |
| **Sex x EE → UB** | -0.050 | 0.024 | 2.054 | 0.040 | Significant |
| **Sex x SI → BI** | 0.076 | 0.022 | 3.416 | 0.001 | Significant |
| **Sex x SI → UB** | 0.043 | 0.021 | 1.984 | 0.047 | Significant |
| **Sex x FC → BI** | -0.145 | 0.028 | 5.112 | 0.000 | Significant |
| **Sex x FC → UB** | 0.033 | 0.023 | 1.479 | 0.139 | Not significant |
| **Sex x HM → UB** | -0.094 | 0.026 | 3.618 | 0.000 | Significant |
| **Sex x HT → BI** | -0.149 | 0.024 | 6.258 | 0.000 | Significant |
| **Sex x HT → UB** | -0.018 | 0.022 | 0.807 | 0.420 | Not significant |
| **Sex x BI → UB** | 0.117 | 0.022 | 5.251 | 0.000 | Significant |
| **Programme x PE → BI** | 0.155 | 0.016 | 9.632 | 0.000 | Significant |
| **Programme x PE → UB** | -0.132 | 0.016 | 8.138 | 0.000 | Significant |
| **Programme x EE → BI** | -0.043 | 0.017 | 2.463 | 0.014 | Significant |
| **Programme x EE → UB** | 0.037 | 0.013 | 2.826 | 0.005 | Significant |
| **Programme x SI → BI** | 0.051 | 0.011 | 4.494 | 0.000 | Significant |
| **Programme x SI → UB** | -0.091 | 0.010 | 9.023 | 0.000 | Significant |
| **Programme x FC → BI** | -0.129 | 0.018 | 7.130 | 0.000 | Significant |
| **Programme x FC → UB** | -0.009 | 0.014 | 0.640 | 0.523 | Not significant |
| **Programme x HM → UB** | -0.024 | 0.017 | 1.356 | 0.175 | Not significant |
| **Programme x HT → BI** | 0.086 | 0.013 | 6.688 | 0.000 | Significant |
| **Programme x HT → UB** | 0.006 | 0.015 | 0.385 | 0.700 | Not significant |
| **Programme x BI → UB** | 0.151 | 0.016 | 9.459 | 0.000 | Significant |

## Discussion

The study examined factors associated with undergraduate students' intention to use ChatGPT and their actual use of the tool in selected higher education institutions in Nigeria. The findings are discussed in relation to UTAUT2 and previous research, with attention to the factors associated with students' intention and actual use.

Performance expectancy (PE) was positively associated with behavioural intention (BI). This indicates that students were more willing to use ChatGPT when they believed it could improve their academic work, support learning and help them complete assignments. This finding agrees with Owan, Mohammed et al. (2025), who identified PE as a significant predictor of students' intention to use ChatGPT for academic purposes. It also agrees with the position of Venkatesh et al. (2012) that perceived usefulness is important in technology acceptance. However, PE had a negative relationship with use behaviour (UB). This suggests that believing ChatGPT is useful does not necessarily lead to more frequent use. Limited internet access, unreliable electricity, concerns about accuracy and uncertainty about acceptable academic use may restrict students' engagement with the tool. These possible explanations require further investigation, as the cross-sectional design does not establish the reasons for the relationship. Universities should therefore improve digital access and provide clear guidance on responsible AI use.

Effort expectancy (EE) was negatively associated with BI but had no significant relationship with UB. This finding differs from the expectation that perceived ease of use encourages technology adoption (Venkatesh et al., 2012). One possible explanation is that students already familiar with digital platforms may not regard ease of use as a major consideration when deciding whether to use ChatGPT. They may be more concerned with its usefulness for learning and completing academic tasks. The negative relationship, however, should not be interpreted as evidence that ease of use discourages adoption in every situation. Rather, the result indicates that EE did not operate in the expected direction in this sample. Training should consequently go beyond explaining how to operate ChatGPT and focus on using it to understand difficult topics, develop ideas and solve academic problems.

Social influence (SI) was positively associated with BI but negatively associated with UB. Encouragement from classmates and lecturers may influence students' willingness to use ChatGPT, but such encouragement does not necessarily translate into regular use. Students may be willing to try the tool while remaining uncertain about its accuracy, academic integrity requirements or the extent to which lecturers permit its use. This finding suggests that intention and actual engagement may respond differently to social expectations. However, the reasons for the negative relationship with UB cannot be established from the present data. Clear communication about acceptable uses of ChatGPT in assignments and research may help students make informed decisions about its use.

Facilitating conditions (FC) were negatively associated with BI but positively associated with UB. This suggests that access to resources and technical support was more closely related to actual use than to students' intention to use ChatGPT. The negative relationship with BI was unexpected, as UTAUT2 generally treats facilitating conditions as supportive of technology adoption (Venkatesh et al., 2012). Students may form intentions based on their perceptions of

ChatGPT before considering the resources required for regular use. Actual use, however, may depend more directly on access to internet services, electricity and suitable devices. These explanations remain tentative, but the result draws attention to the need for reliable digital infrastructure and accessible technical support in Nigerian higher education institutions.

Hedonic motivation (HM) was positively associated with both BI and UB. Students who found ChatGPT enjoyable or interesting were more likely to intend to use it and to report actual use. This agrees with Adeshola and Adepoju (2024), whose research identified educational benefits associated with ChatGPT, and with UTAUT2, which recognises enjoyment as a factor in technology adoption (Venkatesh et al., 2012). ChatGPT's conversational interface and immediate responses may make academic tasks more engaging and allow students to explore ideas at their own pace. Nevertheless, enjoyment should be accompanied by critical evaluation of AI-generated responses and adherence to academic integrity requirements.

Habit (HB) was positively associated with both BI and UB, with a stronger relationship with BI than with UB in terms of the reported effect sizes. Students who had incorporated ChatGPT into their academic routines were more likely to intend to continue using it and to report actual use. This is consistent with UTAUT2, which recognises habit as an important factor in continued technology use (Venkatesh et al., 2012), and with Owan, Chukwu et al. (2025), who linked technology use with students' learning practices. Repeated use may increase familiarity with the tool and make it part of routine academic activities. However, habitual use should not replace independent thought. Lecturers should encourage students to use ChatGPT for explanations, examples and idea development while requiring them to evaluate its responses and take responsibility for their work.

BI was positively associated with UB, supporting the view that intention is an important predictor of actual technology use. Students who intended to use ChatGPT were more likely to report using it for academic activities. This finding agrees with UTAUT2 (Venkatesh et al., 2012) and supports the relevance of BI in explaining students' engagement with the tool. Nevertheless, intention alone may not guarantee actual use, particularly where access to digital resources is limited. The positive relationship between BI and UB therefore needs to be considered alongside the findings for FC and the other predictors.

The moderation results showed that some relationships differed by age, sex and programme of study. Age moderated several relationships involving PE, EE, FC, HM and HB, while sex and programme of study also moderated selected relationships with BI and UB. These results suggest that the factors associated with ChatGPT adoption may not operate in the same way across student groups. However, the direction of some demographic differences depends on how the variables were coded, and the findings do not justify broad conclusions about all male or female students or all academic programmes. Universities should therefore provide AI literacy support across disciplines and consider differences in students' access, experience and learning needs when planning such programmes.

In general, the findings indicate that students' intention to use ChatGPT and their actual use were associated with different factors. PE was related to BI, while HM and HB were related to both BI and UB. FC was positively associated with UB, and BI was positively associated with actual use. These results suggest that promoting responsible ChatGPT use requires more than encouraging students to adopt the tool. Universities should improve access to digital resources, provide clear

guidance on acceptable academic use and support students in developing the skills needed to assess AI-generated information critically.

### Limitations and future research directions

Several limitations should be considered when interpreting the findings. First, the study involved undergraduates in selected Nigerian institutions, which may limit the generalisability of the findings to other institutions and countries. Future research should include more institutions across Nigeria and other African countries to examine regional differences. Second, the cross-sectional design captured responses at one point in time and could not establish changes in students' perceptions and use of ChatGPT. Longitudinal or mixed-methods research are needed to examine how continued exposure and changes in institutional attitudes affect the use of AI tools. Third, reliance on self-reported questionnaire data may have introduced response bias. Students may have overestimated or inaccurately reported their use of ChatGPT. Future studies could combine questionnaires with usage records, teacher assessments or direct observation.

Fourth, the quantitative approach did not fully explain why students held different views about ChatGPT under similar conditions. Interviews and focus group discussions could offer further understanding of their motivations, concerns and ethical views. Fifth, institutional and policy factors, including lecturers' views, departmental rules and national guidelines, were not examined. Future research should include these variables. Sixth, although the sample was large (N = 8,496), no oversampling was undertaken to ensure greater representation of particular groups. Future studies should assess sample composition when interpreting subgroup differences and representativeness. Finally, AI technology continues to change rapidly, and students' experiences may change accordingly. Future research should compare newer versions of ChatGPT and similar tools, while combining broader institutional coverage, longitudinal designs and mixed methods to examine technological, institutional and policy influences on academic use.

## Conclusion

This study examined factors associated with undergraduate students' behavioural intention to use ChatGPT and their actual use of the tool in selected higher education institutions in Cross River State, Nigeria. Guided by UTAUT2, the study assessed the relationships between students' beliefs, motivations and personal characteristics and their use of ChatGPT for learning. Performance expectancy, hedonic motivation and habit significantly predicted behavioural intention, while facilitating conditions, hedonic motivation, habit and behavioural intention significantly predicted actual use. Enjoyment and habit were important predictors of use, whereas effort expectancy had little effect. Social influence was associated with intention but did not necessarily translate into frequent use. Facilitating conditions were more strongly related to actual use than to intention, indicating the importance of internet access, electricity and digital devices. Behavioural intention also mediated the relationships between acceptance factors and use. Age, sex and programme of study moderated some relationships. The study extends understanding of UTAUT2 in a developing-country setting. Universities should improve digital infrastructure and establish clear policies for responsible academic use of ChatGPT. Training should guide students and lecturers to use the tool as a learning aid rather than a substitute for critical thinking and independent work. Institutional policies should also address ethical use in coursework and

research. These measures may benefit other developing countries facing similar educational and technological challenges.

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Author Contributions Based on CRediT Taxonomy: VJO: Conceptualisation, writing – original draft, methodology, data collection, data analysis, visualisation, editing, and final approval. IAM: Conceptualisation, writing – original draft, data collection, technical support, editing, and final approval. AB: Data collection, project administration, software, and final approval. TAS: Data collection, supervision, and final approval. MVO: Data collection, writing - editing and review, and final approval.

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