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Multi group analysis of demographic differences in higher education students ChatGPT use behaviour within a modified UTAUT2 model

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Abstract
Although extensive research has examined AI integration in education and the UTAUT2 model, few studies have explored ChatGPT adoption with demographic variables in Nigeria and other African contexts. Prior studies have analyzed the impacts UTAUT variables have on students' behavioral intention and use of ChatGPT, yet little is known about how these relationships differ by demographic profiles. This study addresses that gap by investigating the influence of factors such as age, sex, and programme of study on these associations among Nigerian higher education students. A cross-sectional correlational design was used and data were collected from 8,496 students across various tertiary institutions in Nigeria, using a structured questionnaire. Data were gathered electronically between October 13, 2023, and February 14, 2024. Multigroup analysis within the framework of Partial Least Squares Structural Equation Modelling (PLS-SEM) was performed. Both measurement and structural model metrics are reported for all subgroups. Findings indicate that performance expectancy is associated with higher intention to use ChatGPT, particularly among males, older students, and those with advanced qualifications, while its relationship with actual use varies across age groups. Effort expectancy and social influence showed differing associations with intention and use depending on demographic characteristics. Facilitating conditions were generally linked to greater actual use, and both hedonic motivation and habit were consistently associated with intention and behavior. These results provide empirical evidence of demographic variations in ChatGPT adoption among Nigerian students and suggest that interventions promoting AI tools should consider these differences.

Keywords Age, ChatGPT, Higher education, PLS-SEM, Sex, Technology acceptance

1 Introduction

Artificial intelligence (AI) continues to influence many areas of life, including web search engines, mobile applications, and healthcare systems [54], all of which have significant implications for teaching and learning. In the education sector, AI has been applied

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through tools such as chatbots [12, 39], intelligent tutoring systems, learning management systems, and automated grading tools (Heffernan & Heffernan [20, 26]. One of the most widely researched AI innovations is the Chat Generative Pre-Trained Transformer (ChatGPT).

ChatGPT is a large language model that uses deep learning and complex algorithms to perform language-related tasks such as text generation, question answering, and translation [44]. It also interprets context to produce responses that resemble human language [36]. Within two months of its release on 30 November 2022, ChatGPT reached 100 million users and recorded approximately 590 million visits in January 2023 (The Guardian 2023). As a tool that supports teaching and learning, ChatGPT enhances students' learning experiences, provides new ways to express ideas, and generates personalised feedback based on instructional input [28]. Despite these benefits, ChatGPT presents challenges such as plagiarism concerns [13, 47], cognitive bias arising from its inability to discern factual accuracy [31, 35], and issues related to privacy and ethics [36, 53].

Existing literature revealed that the extended UTAUT has been used to understand acceptance and use of technology among higher education students. For example, the UTAUT2 model has been used to understand students' acceptance and use of technology in different fields like ChatGPT [9, 56], ICT in tourism [4], e-learning [1, 3, 51]; mobile applications [6, 41]; immersive virtual and augmented reality [21]; and learning management systems [5, 7, 33].

Recent studies have shown the increasing influence of artificial intelligence in higher education. [29] explained that ChatGPT can promote technological sustainability by supporting personalised learning, improving feedback systems, and simplifying assessment processes. They also drew attention to the need for clear ethical and institutional guidelines when using such tools. In a related study, [2] discussed how ChatGPT can improve teaching and learning efficiency and assist students in developing writing skills, while warning that issues of academic honesty, trust, and social inequality require careful management. [40] conducted a systematic review of student engagement in technology-enhanced environments such as the metaverse. Their findings indicated that interactive features, learner motivation, and design quality influence how students participate in digital learning spaces. Together, these studies provide a foundation for understanding how artificial intelligence supports active learning and responsible educational innovation.

Most research on technology use has been carried out outside Africa and seldom focuses on ChatGPT. Few studies have looked at how factors such as age, gender, and programme of study affect students' intention to use ChatGPT. As a result, little is known about how students in developing countries use artificial intelligence tools for learning. This study addresses this issue by applying an extended UTAUT2 model to examine how demographic factors influence the intention of higher education students to use ChatGPT. Focusing on Nigerian universities, the study adds to current knowledge on technology use in developing regions. It also provides practical evidence of how age, gender, and academic discipline affect students' willingness to adopt artificial intelligence tools. The results will guide decisions on policy, teaching methods, and fair access to digital resources in African higher education.

2 Theoretical framework

The extended unified theory of acceptance and use of technology (UTAUT2) model is designed to study users' acceptance and use of technology and has notably improved explanations of both behavioral intention and technology adoption. Consequently, it is one of the most frequently cited models in the field. UTAUT2 includes seven core variables—effort expectancy, performance expectancy, social influence, facilitating conditions, habit, hedonic motivation, and price value—and three moderating variables: age, experience, and gender [46]. In this study, however, "experience" is replaced by "programme of study" given that respondents are higher education students. Additionally, as [18] noted that many studies focus on only select UTAUT2 elements and largely ignore demographic variables, we examined the influence of age, gender, and programme of study. Price value was excluded because ChatGPT offers a free version.

Age is a key moderator in UTAUT2, influencing technology acceptance and use. Younger individuals typically adopt and use new technologies more easily due to their technological savvy, whereas older users tend to face more challenges [60]. [55] further support this, noting that younger users are more technology-ready and less swayed by technology characteristics compared to older users.

Gender relates to the socially constructed roles assigned to males and females. Studies have shown that male students tend to spend more time using technology [30] and generally have a more positive outlook on technology adoption than female students [52]. Therefore, gender is treated as a moderating variable that could influence the relationship among UTAUT2 constructs.

"Programme of study" refers to the academic degree higher education students pursue. In Nigerian tertiary institutions, students obtain various qualifications ranging from the Ordinary National Diploma (OND) and Higher National Diploma (HND) from polytechnics or monotechnics, to the Nigeria Certificate in Education (NCE) from Colleges of Education. Universities award Bachelor's degrees for undergraduate studies, with Master's and Doctoral degrees offered as postgraduate qualifications. Despite the limited research on the mediating role of programme of study in the UTAUT2 framework, this study aims to fill that gap by assessing its impact on the relationships among UTAUT2 constructs. Based on these considerations, the conceptual framework for this study is presented in Fig. 1.

3 Hypothesis development

3.1 Performance expectancy (PE)

Performance expectancy (PE) refers to the degree to which individuals believe that using a technology will improve their task performance [59]; Venkatesh et al.. 61 identified PE as the strongest determinant of behavioural intention to adopt new technology, a finding reinforced by [55]. In this study, PE represents the extent to which higher education students perceive ChatGPT as useful for learning, research, and related academic tasks. Recent studies further highlight that the perceived usefulness of generative AI tools such as ChatGPT significantly shapes students' adoption decisions and academic engagement patterns [2, 29, 40]. Consequently, when students perceive ChatGPT as beneficial, their intention to adopt and use it tends to increase.

Empirical evidence consistently positions PE as a central construct in explaining technology adoption behaviour. For example, recent Nigerian studies have shown that PE

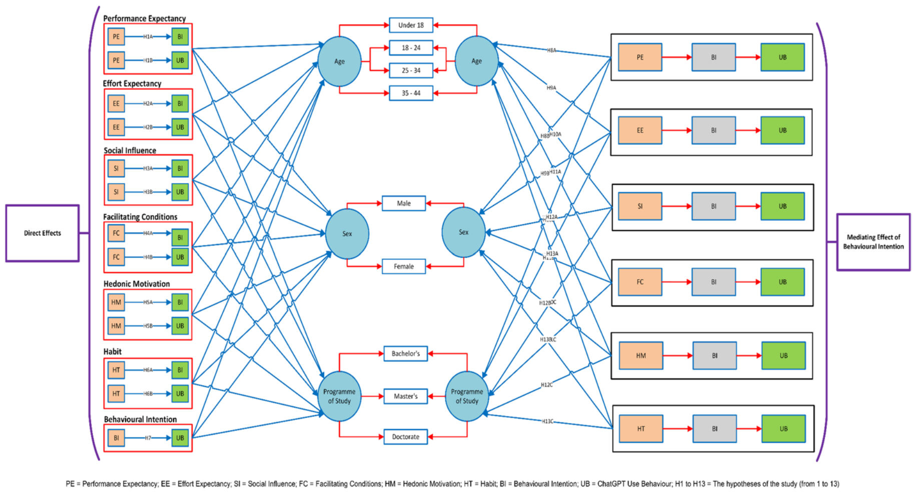

Fig. 1 Conceptual Framework of the study

significantly predicts students' behavioural intention to use ChatGPT for academic tasks and information seeking [44]. Similarly, [45] reported that perceived usefulness plays a critical role in students' acceptance of AI tools for self-directed learning. Ofem et al. [43] further observed that students' performance beliefs influence both positive and opportunistic patterns of ChatGPT use, revealing the breadth of its perceived utility among Nigerian students.

The influence of PE on user intention has been shown to vary across demographic factors. [59] observed that age moderates the effect of PE on behavioural intention (BI) in favour of younger users. [30] found a similar moderating effect but in favour of older users, while [32, 38] reported stronger effects among younger students. [55] observed that PE significantly predicts user intention for individuals older than 35, whereas Chang et al. [10] confirmed moderation favouring younger individuals. [50] also found age effects in integrated licensing service usage. In contrast, [24, 41, 46] found no significant moderation by age. The current study builds on these mixed findings by examining these effects in the underexplored Nigerian higher education context, thereby addressing a clear research gap on age-based moderations in generative AI adoption.

Regarding gender, [59] found that men experience stronger PE effects on BI, a finding echoed by [24, 30, 32, 38, 65], 10, 15, 50, 55]. [41, 46] reported no moderation by gender. Understanding how gender shapes PE in ChatGPT use is particularly relevant in Nigeria, where gendered differences in digital tool adoption have been documented but rarely linked to AI tools for learning [40].

For programme of study, [27] found no moderation effect, and [57] also reported no significant moderating influence of education level on PE–BI relationships in ChatGPT usage. However, empirical investigations in the African context remain scarce, underscoring the need for deeper exploration of this dimension. Based on these considerations, the following hypotheses were formulated:

	Null (H_0)	Alternative (H_1)
H1A	The direct effect of performance expectancy (PE) on behavioural intention to use ChatGPT does not differ across students' age, sex, and programme of study.	The direct effect of performance expectancy (PE) on behavioural intention to use ChatGPT differs across students' age, sex, and programme of study.

	Null (H_0)	Alternative (H_1)
H1B	The direct effect of performance expectancy (PE) on ChatGPT use behaviour does not differ across students' age, sex, and programme of study.	The direct effect of performance expectancy (PE) on ChatGPT use behaviour differs across students' age, sex, and programme of study.

3.2 Effort expectancy (EE)

Effort expectancy (EE) refers to the ease associated with using a technology and is recognized as a direct predictor of a user's intention to adopt a technology [55, 59]. Chang et al. [10] observed that users are more likely to accept and use a technology when it is user-friendly, offering an intuitive interface and clear learning guidance. In this study, EE reflects the degree to which higher education students find ChatGPT easy to use. In other words, if students find ChatGPT straightforward and uncomplicated, they are more likely to intend to use and incorporate it into their instructional activities.

The literature presents mixed evidence regarding the moderating role of demographic factors on the relationship between EE and behavioral intention (BI). Several studies report that age does not significantly influence the relationship between EE and BI. For instance, [11, 24, 32, 41, 46] all found that age does not moderate the impact of EE on BI. In contrast, [59] indicated that age moderates the relationship between EE and BI in favor of older individuals. Similarly, [38] reported that age moderates the relationship in the context of e-book usage, and [10] and [55] also noted a moderating effect of age, with [55] finding that EE serves as a significant antecedent of BI for individuals older than 35 compared to those younger than 35.

In terms of gender, several studies indicate that gender moderates the effect of EE on BI in favor of women. [59] noted that the moderating effect of gender on the relationship between EE and BI favors female users. This finding is supported by [24, 32, 38], and Chang et al. [10], who all observed that the influence of EE on BI is moderated by gender. [55] further demonstrated that the relationship between EE and usage intention is moderated by gender in favor of female users. However, contrasting results were found by [11, 46], Chang et al. [10], and [15], who reported that gender does not significantly moderate the effect of EE on BI.

Regarding the programme of study, [27] found that the influence of EE on BI is not moderated by education level. On the other hand, [57] conducted a study in Poland and Egypt that revealed a moderating effect of education level on the relationship between EE and BI among Polish students, while no such moderation was observed among Egyptian students.

Given these varied findings on the role of demographic variables in the UTAUT2 model, there is a clear need for further investigation. In particular, more research is required to ascertain the moderating effects of both age and gender. Moreover, considering the limited studies on the influence of programme of study on the relationship between EE and BI, additional research is necessary to address these gaps. In light of the foregoing discussion, the following hypotheses were formulated:

	Null (H_0)	Alternative (H_1)
H2A	The direct effect of effort expectancy (EE) on behavioural intention to use ChatGPT does not differ across students' age, sex, and programme of study.	The direct effect of effort expectancy (EE) on behavioural intention to use ChatGPT differs across students' age, sex, and programme of study.

	Null (H_0)	Alternative (H_1)
H2B	The direct effect of effort expectancy (EE) on ChatGPT use behaviour does not differ across students' age, sex, and programme of study.	The direct effect of effort expectancy (EE) on ChatGPT use behaviour differs across students' age, sex, and programme of study.

3.3 Social influence (SI)

Social influence (SI) refers to the extent to which individuals believe that important others think they should use a particular technology [59]. Chang et al. [10] noted that factors such as peer recommendations, support from management, and employer pressure can affect employees' intention to use property management systems. [55] found that social influence positively and significantly affects both behavioral intention (BI) and use behaviour (UB). In this study, the adoption of ChatGPT by students and lecturers is expected to motivate others to use and adopt it.

The literature offers varied findings regarding the moderating role of demographic variables on the SI–BI relationship. Concerning age, some studies indicate a moderating effect. [59] reported that age moderates the influence of SI on BI in favor of women, while [24, 30] similarly observed that age plays a moderating role. [11, 38] also found that age influences the SI–BI relationship, particularly in contexts such as e-book use. In contrast, other studies by [10, 32, 41, 46, 55] did not detect any moderating effect of age on the relationship between SI and BI.

The moderating role of gender in the SI–BI relationship is similarly inconclusive. On one side, research by [24, 30, 32, 59] indicates that gender moderates this relationship in favor of women, a finding also supported by [38] in the context of e-book use. On the other side, studies by Chang et al. [10, 11, 41, 46, 50], along with findings from [15, 55], suggest that gender does not significantly moderate the influence of SI on BI.

Regarding programme of study, [27] found that education level does not moderate the effect of SI on BI. However, research by [57] conducted in both Poland and Egypt showed that education level moderated the SI–BI relationship in both contexts. Given these inconsistent findings on the moderating effects of age and gender, and the limited research on the role of programme of study, there is a clear need for further investigation into how these demographic variables affect students' intention to use ChatGPT. In response to these gaps, the present study examines the moderating influence of age, gender, and programme of study on the relationship between social influence and behavioral intention. Based on the discussion above, we formulated the following hypotheses:

	Null (H_0)	Alternative (H_1)
H3A	The direct effect of social influence (SI) on behavioural intention to use ChatGPT does not differ across students' age, sex, and programme of study.	The direct effect of social influence (SI) on behavioural intention to use ChatGPT differs across students' age, sex, and programme of study.
H3B	The direct effect of social influence (SI) on ChatGPT use behaviour does not differ across students' age, sex, and programme of study.	The direct effect of social influence (SI) on ChatGPT use behaviour differs across students' age, sex, and programme of study.

3.4 Facilitating conditions (FC)

Facilitating conditions (FC) refer to the degree individuals have confidence that the necessary resources are in place to enable them use a new technology [59]. In the UTAUT2 framework, FC is posited to have a direct impact on the behavioral intention (BI) to use new technology. This occurs because a higher availability and accessibility of resources, such as materials, knowledge, and support, increases users' willingness to adopt a technology [55]. In the present study, FC is applied to evaluate how well the infrastructure and support systems facilitate higher education students' use of ChatGPT.

The literature on the moderating effects of age and gender on the relationship between FC and BI or use behavior (UB) presents mixed findings. Several studies suggest that age plays a moderating role. For instance, [32] reported that the effect of FC on the intention to use Elluminate was more pronounced among older students. [24] also found that age moderates the relationship between FC and BI, while [38] observed a similar moderating influence in the context of e-book usage. [48] further noted that age moderated the relationship between FC and BI for the use of a portable scanner app, favoring younger users, and Chang et al. [10] confirmed that age affects both behavioral intention and use behavior with respect to FC. Conversely, studies by [41, 46, 55] did not find age to be a significant moderator of the relationship between FC and BI.

The moderating effect of gender on the relationship between FC and BI has similarly yielded inconsistent outcomes. [38] and Chang et al. (2019) revealed that gender moderates this relationship, with some findings indicating a notable influence. [48] observed a significant moderating effect of gender on the FC–BI relationship in the context of a portable scanner app, and [30] noted that gender might play a role. [65] provided evidence that gender significantly influences the FC–BI relationship in favor of men. However, other studies by [24, 41, 46, 55] reported no significant moderating effect of gender.

In terms of education level, [27] found that the influence of FC on BI is not moderated by education level. In contrast, [57] conducted research in both Poland and Egypt, revealing that education level moderated the relationship between FC and use behavior on the Polish side, while no such moderation was observed in Egypt. Given these contradictory results, particularly concerning the moderating influences of age, gender, and programme of study (as a proxy for education level), it is clear that the current body of research does not offer a unified conclusion on the subject. Furthermore, the scarcity of studies examining the moderating effect of programme of study on the relationship between FC and both BI and UB calls for additional research. In view of this, we have developed the following hypotheses to further investigate the impact of these demographic variables on students' intentions to use ChatGPT.

	Null (H_0)	Alternative (H_1)
H4A	The direct effect of facilitating conditions (FC) on behavioural intention to use ChatGPT does not differ across students' age, sex, and programme of study.	The direct effect of facilitating conditions (FC) on behavioural intention to use ChatGPT differs across students' age, sex, and programme of study.
H4B	The direct effect of facilitating conditions (FC) on ChatGPT use behaviour does not differ across students' age, sex, and programme of study.	The direct effect of facilitating conditions (FC) on ChatGPT use behaviour differs across students' age, sex, and programme of study.

3.5 Hedonic motivation (HM)

Hedonic motivation (HM) refers to the feelings of cheerfulness, joy, or enjoyment that arise from using a technology, and it is regarded as a significant determinant of users' intention to adopt that technology [60]. In this study, a higher level of perceived hedonic motivation among higher education students is expected to correlate with a greater intention to use ChatGPT. The platform's innovative ability to deliver rapid responses and address queries can evoke excitement and pleasure, thereby encouraging its adoption.

The literature indicates that the relationship between HM and both behavioral intention (BI) and use behavior (UB) may be influenced by demographic factors. Concerning age, several studies suggest that it can moderate the HM–BI relationship. [38] observed that age moderates the association between HM and BI in the context of e-book use, while [24] reported a similar moderating effect. Chang et al. [10] also found that the impact of HM on BI is affected by age, and [55] further demonstrated that HM significantly predicts BI among younger users. In contrast, other studies have shown no moderating effect of age on the HM–BI relationship. For instance, [41, 46, 48] found that age does not moderate this relationship, suggesting that the influence of HM on students' intentions may be consistent across different age groups.

The moderating role of gender in the relationship between HM and BI has also received attention. Some studies report that gender does have a moderating effect. [38] found that gender influences the HM–BI relationship, and Chang et al. [10] similarly reported that the impact of HM on BI is moderated by gender. [55] revealed that this relationship is moderated by gender in favor of male users. However, there are studies that contradict these findings. Research by [24, 41, 46] along with findings from [48], indicate that gender does not significantly moderate the influence of HM on BI, leaving the role of gender as a moderator inconclusive.

With respect to programme of study, [27] found that education level does not moderate the effect of HM on BI. This finding, coupled with the conflicting evidence regarding the moderating effects of age and gender, highlights the need for further investigation. The limited research on the moderating influence of programme of study compounds this uncertainty, as few studies have explored its impact on the relationship between HM and BI or UB. Given these varied and sometimes contradictory results, it is imperative to further examine how demographic variables such as age, gender, and programme of study affect higher education students' intention to use ChatGPT. This study addresses these gaps by testing the moderating effects of these factors on the relationship between hedonic motivation and both behavioral intention and use behavior. Consequently, the following hypotheses have been formulated:

	Null (H_0)	**Alternative (H_1)**
H5A	The direct effect of hedonic motivation (HM) on behavioural intention to use ChatGPT does not differ across students' age, sex, and programme of study.	The direct effect of hedonic motivation (HM) on behavioural intention to use ChatGPT differs across students' age, sex, and programme of study.
H5B	The direct effect of hedonic motivation (HM) on ChatGPT use behaviour does not differ across students' age, sex, and programme of study.	The direct effect of hedonic motivation (HM) on ChatGPT use behaviour differs across students' age, sex, and programme of study.

3.6 Habit (HT)

Habit, as incorporated into UTAUT2, is defined as an unconscious or automatic behavior that develops from prior performance, where actions are performed automatically due to learning [55, 60]. Habit can influence usage intention, with its impact on behavioral intention (BI) and use behavior (UB) potentially moderated by demographic variables such as age, gender, and programme of study.

Several studies have examined the moderating role of age on the relationship between habit and technology usage. For instance, [38] found that age moderates the relationship between habit and both usage intention and use behavior in the context of e-book use. Chang et al. [10] also reported that the impact of habit on BI and UB is moderated by age. [48] observed that age moderated the relationship between habit and BI for a portable scanner app in favor of younger users. In contrast, other studies have found no significant moderating effect of age. [41, 46, 48] reported that age did not moderate the influence of habit on BI or UB. Similarly, [55] indicated that age did not moderate the relationship between habit and usage intention.

Regarding gender, [38] and Chang et al. [10] observed that gender moderates the relationship between habit and BI in the context of e-book use and other technologies. However, findings from [41, 46, 48, 55] suggest that gender does not moderate the influence of habit on BI or UB.

Concerning programme of study, [27] found that education level does not moderate the effect of habit on BI. Given these conflicting results and the limited research on the moderating role of programme of study, further empirical studies are necessary, especially among higher education students who increasingly rely on large language models like ChatGPT. Consequently, the following hypotheses have been formulated:

	Null (H_0)	**Alternative (H_1)**
H6A	The direct effect of habit (HT) on behavioural intention to use ChatGPT does not differ across students' age, sex, and programme of study.	The direct effect of habit (HT) on behavioural intention to use ChatGPT differs across students' age, sex, and programme of study.
H6B	The direct effect of habit (HT) on ChatGPT use behaviour does not differ across students' age, sex, and programme of study.	The direct effect of habit (HT) on ChatGPT use behaviour differs across students' age, sex, and programme of study.

3.7 Behavioural intention (BI)

Behavioural intention (BI) is defined as the extent to which an individual is willing to adopt a technology. In this study, BI represents a student's deliberate plan to accept, implement, and use ChatGPT to meet educational objectives. Based on the original UTAUT model, BI is posited as a mediating variable to examine whether students intend to continue using ChatGPT for learning [7]. Today's higher education students, being technologically savvy and digitally literate, use new technologies regardless of age, sex, or programme of study. To the best of the researchers' knowledge, no empirical study has examined BI's effect on ChatGPT use behavior considering these demographics. Hence, the following hypothesis was formulated:

	Null (H_0)	**Alternative (H_1)**
H7	The direct effect of behavioural intention (BI) on ChatGPT use behaviour does not differ across students' age, sex, and programme of study.	The direct effect of behavioural intention (BI) on ChatGPT use behaviour differs across students' age, sex, and programme of study.

3.8 Conceptual framework

Figure 1 presents the conceptual model adapted from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The model explains how performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit influence behavioural intention and actual use behaviour. Behavioural intention directly affects use behaviour, representing the central pathway through which technology acceptance occurs among students.The model also includes age, sex, and programme of study as moderating variables to assess whether these demographic characteristics change the strength or direction of the relationships among the main constructs. Each pathway corresponds to a specific hypothesis (H1A to H7), indicating the theoretical relationships tested in the study. The framework provides a clear basis for understanding how individual perceptions, social factors, and enabling conditions combine to influence students' behavioural decisions regarding technology use.

4 Methods

A cross-sectional correlational design was adopted to examine the relationships among extended UTAUT constructs—namely performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habits—and higher education students' behavioral intentions and usage of ChatGPT in Nigeria. In addition, demographic variables such as age, sex, and programme of study were incorporated into the analysis. This research design permitted the exploration of these associations without manipulating the variables, thereby avoiding causal claims [14, 45]. Given the practical constraints in our setting, this approach proved suitable for assessing the theoretical framework within a natural academic environment among Nigerian students.

4.1 Participants

A total of 8,496 higher education students participated in the study. Eligible participants were students enrolled in any Nigerian tertiary institution, including colleges of education, monotechnics, polytechnics, and universities, irrespective of ownership (federal, state, missionary, or private).

A stratified convenience sampling approach was used to ensure representation across different institutional categories and ownership types. First, the researchers created a sampling frame that reflected Nigeria's higher education structure, categorising institutions into four strata: colleges, monotechnics, polytechnics, and universities. Within each stratum, at least five institutions were purposively identified from each of the six geopolitical zones (North-Central, North-East, North-West, South-East, South-South, and South-West) to achieve regional balance. Institutional representatives such as departmental heads, student union officials, and course advisers were contacted to assist in sharing the survey link. The questionnaire was distributed electronically via institutional mailing lists, academic WhatsApp groups, Telegram platforms, and official student associations. Participation was voluntary, and no incentives were offered. Responses were monitored to ensure that no single institution or ownership type was overrepresented, resulting in a balanced dataset across the different strata.

Age distribution was as follows: 0.8% ($n = 72$) under 18, 36.4% ($n = 3{,}096$) aged 18–24, 38.1% ($n = 3{,}240$) aged 25–34, and 24.6% ($n = 2{,}088$) aged 35–44. For sex, 54.0% ($n = 4{,}584$) were male and 46.0% ($n = 3{,}912$) female. Regarding programme of study, 33.6% ($n = 2{,}856$) were bachelor's students, 26.6% ($n = 2{,}256$) master's, 19.2% ($n = 1{,}632$) doctoral, 8.8% ($n = 744$) OND, 8.8% ($n = 744$) HND, 1.1% ($n = 96$) NCE, and 2.0% ($n = 168$) PGD students.

4.2 Instrument and measures

Data were collected through an online survey titled the *Higher Education Students' ChatGPT Utilisation Questionnaire* (HESCUQ), designed using Google Forms. The instrument consisted of three sections: (1) a cover letter containing the study purpose, informed consent, and submission tracking; (2) demographic information (age, sex, and programme of study); and (3) items measuring the UTAUT2 constructs. These constructs included Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HB), Behavioural Intention (BI), and ChatGPT Use Behaviour (UB). Items were adapted from prior validated instruments in related studies and contextualised for Nigerian higher education students. To maintain transparency and academic integrity, the full list of subscales, sample items, and original references has been previously reported in a related publication by the research team [44]. Hence, these details are not repeated here to avoid duplication.

To ensure contextual suitability, several modifications were made during the adaptation process. Terms and examples were adjusted to reflect the linguistic and educational realities of Nigerian higher education. For example, the term "coursework" was preferred to "projects," and "lecturers" replaced "faculty" to align with local usage. Mentions of "digital learning tools" were refined to include platforms familiar to Nigerian students, such as WhatsApp, Google Workspace, and institutional learning management systems. These adaptations aimed to preserve conceptual accuracy while enhancing clarity and cultural relevance. The adaptation followed established cross-cultural instrument development guidelines [8, 16], ensuring semantic equivalence and content validity.

Responses were recorded on a four-point Likert scale ranging from strongly disagree (1) to strongly agree (4). The initial draft of the instrument was reviewed by a panel of seven experts (three psychometrists and four educational technologists) to ensure face and content validity. The item-level content validity indices (I-CVIs) for clarity ranged from 0.74 to 0.99 and for relevance from 0.83 to 0.99, prompting revisions of items scoring below 0.80 [34].

To further contextualise the instrument, a focus group comprising 15 higher education students was conducted. Participants provided detailed qualitative feedback on the comprehensibility and contextual relevance of the items. Specifically, they suggested (a) simplifying academic and technological terms such as *"productivity enhancement"* and *"interactive interface"* into more familiar expressions like *"helping me do my schoolwork faster"* and *"easy to use"*; (b) replacing references to "institutional systems" with "school platforms" to reflect local terminology; and (c) rewording some behavioural intention items to better fit Nigerian academic settings (e.g., substituting "course projects" with "assignments or reports"). These suggestions improved linguistic clarity, reduced ambiguity, and enhanced cultural and contextual alignment with Nigerian higher education practices.

Based on this feedback, two redundant items were removed and several were rephrased for clarity, yielding a 40-item instrument for the main study. Exploratory factor analysis using principal axis factoring with promax rotation confirmed the eight-factor structure, explaining 54.28% of the total variance (KMO = 0.926; Bartlett's test of sphericity, $\chi^2(703) = 176922.96$, $p < .001$). To minimise common method bias, anonymity and item separation techniques were applied [37, 49].

4.3 Data collection procedure

Participation was voluntary and written informed consent was obtained electronically. Ethical clearance was waived in line with national guidance [22]. Participants were informed that results would be reported in aggregate and that personally identifiable information would be deleted after analysis and publication.

Email addresses were requested only to verify unique submissions. The verification process proceeded as follows. First, survey responses and email addresses were exported into two separate files: (a) the response file (responses linked to a study ID only) and (b) the verification file (email address linked to the same study ID). The verification file was stored separately on a password-protected device and access was limited to the lead investigator and the data manager. Duplicate submissions were identified by matching email addresses and submission timestamps; where duplicates occurred, the earliest complete response was retained and subsequent entries were removed. After verification, the verification file (email-to-ID mapping) was permanently delinked from the response file and deleted, leaving an analytic dataset that contained only non-identifiable study IDs and survey responses. At no point during analysis did the research team use email addresses together with survey responses. All files were stored on a password-protected computer with up-to-date security software and were deleted after analysis and publication, as stated in the consent information. These procedures ensured that the final dataset contained no personally identifiable information.

Data collection took place via a dedicated Telegram group. After contacting tertiary institutions, a group of 10,161 students was formed and the survey link was circulated there, yielding 8,496 valid responses collected between 13 October 2023 and 14 February 2024 [19, 63].

5 Results

This study investigates whether the predicted relationships in our conceptual model vary across different demographic groups. A previous publication from this project confirmed that the model works well for the overall sample [44]. In the present work, we examine each subgroup separately to determine if the relationships differ among them. This way, we can observe how each group responds to the model's constructs and note any variations in the effects for diagnostic purposes.

5.1 Measurement model

5.1.1 Outer loadings

Table 1 presents the factor loadings for items measuring each construct, categorized by gender, age, and education level. The recommended outer loading threshold is 0.708 for indicator reliability, though loadings above 0.50 are acceptable when internal consistency and convergent validity criteria are met [25]. For Performance Expectancy (PE), male loadings ranged from 0.80 to 0.84 and female loadings from 0.72 to 0.83. By age, PE loadings were 0.73–0.84 (18–24 years), 0.74–0.83 (25–34 years), and 0.81–0.89 (35–44

Table 1 Factor loadings for UTAUT2 constructs (PE, EE, SI, FC, HM, BI, and UB) across demographic subgroups (gender, age, and education level)

Outer loadings	A	B	C	D	E	F	G	H
PE2	0.802	0.766	0.736	0.816	0.820	0.800	0.807	0.849
PE3	0.817	0.725	0.743	0.812	0.765	0.656	0.813	0.893
PE4	0.837	0.824	0.793	0.832	0.884	0.750	0.854	0.890
PE5	0.820	0.827	0.830	0.804	0.829	0.814	0.707	0.918
EE1	0.810	0.600	0.763	0.685	0.840	0.823	0.703	0.824
EE2	0.848	0.801	0.899	0.836	0.689	0.851	0.810	0.858
EE5	0.846	0.841	0.762	0.795	0.924	0.781	0.900	0.822
SI2	0.852	0.750	0.896	0.727	0.869	0.856	0.823	0.762
SI3	0.803	0.702	0.683	0.795	0.757	0.703	0.742	0.858
SI4	0.750	0.679	0.568	0.740	0.781	0.789	0.709	0.623
FC1	0.814	0.799	0.813	0.801	0.790	0.861	0.835	0.732
FC2	0.834	0.805	0.815	0.755	0.883	0.814	0.795	0.842
FC3	0.825	0.825	0.814	0.864	0.805	0.800	0.818	0.884
FC4	0.729	0.704	0.732	0.695	0.705	0.746	0.578	0.835
HM1	0.826	0.775	0.777	0.816	0.836	0.792	0.807	0.839
HM2	0.815	0.683	0.703	0.794	0.814	0.770	0.812	0.830
HM3	0.747	0.832	0.819	0.706	0.850	0.749	0.771	0.803
HM4	0.799	0.783	0.788	0.799	0.788	0.794	0.805	0.856
HM5	0.875	0.827	0.861	0.835	0.855	0.867	0.844	0.854
HB1	0.826	0.826	0.857	0.818	0.741	0.828	0.797	0.859
HB2	0.911	0.881	0.874	0.892	0.928	0.893	0.921	0.921
HB3	0.910	0.870	0.873	0.907	0.881	0.895	0.893	0.887
HB4	0.832	0.780	0.819	0.805	0.804	0.845	0.859	0.739
BI1	0.824	0.684	0.726	0.800	0.824	0.816	0.769	0.844
BI2	0.861	0.857	0.860	0.838	0.878	0.823	0.888	0.912
BI5	0.832	0.852	0.874	0.778	0.878	0.829	0.740	0.923
UB3	0.822	0.789	0.819	0.818	0.767	0.811	0.809	0.866
UB5	0.860	0.850	0.861	0.846	0.836	0.853	0.799	0.912
UB6	0.881	0.843	0.842	0.889	0.829	0.848	0.860	0.890

Notes: A = Male; B = Female; C = 18 to 24 years; D = 25 to 34 years; E = 35 to 44 years; F = Bachelor's; G = Master's; H = PhD; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; HT = Habit; HM = Hedonic Motivation; UB = ChatGPT Use Behaviour

years). Educationally, loadings ranged from 0.80 to 0.85 for Bachelor's, 0.75–0.84 for Master's, and 0.80–0.92 for PhD holders. Effort Expectancy (EE) items loaded between 0.81 and 0.85 for males and 0.60–0.85 for females. Age-wise, values were 0.60–0.89 (18–24), 0.68–0.85 (25–34), and 0.69–0.92 (35–44); loadings for Bachelor's, Master's, and PhD holders were 0.70–0.85, 0.67–0.84, and 0.81–0.92, respectively.

Social Influence (SI) items ranged from 0.75 to 0.85 for males and 0.70–0.86 for females. For age groups, loadings were 0.70–0.89 (18–24), 0.72–0.87 (25–34), and 0.75–0.89 (35–44), while educational group loadings were 0.74–0.85 (Bachelor's), 0.75–0.86 (Master's), and 0.75–0.88 (PhD). Facilitating Conditions (FC) items yielded loadings of 0.79–0.86 (males) and 0.73–0.84 (females). Age-related loadings ranged from 0.70 to 0.86 (18–24), 0.70–0.88 (25–34), to 0.73–0.88 (35–44), and educationally, 0.79–0.88 (Bachelor's), 0.75–0.88 (Master's), and 0.78–0.91 (PhD).

Table 1 also shows that Hedonic Motivation (HM) items consistently loaded 0.75–0.87 across genders, with age loadings of 0.68–0.86 (18–24), 0.69–0.87 (25–34), and 0.74–0.87 (35–44), and education loadings of 0.75–0.87 (Bachelor's), 0.75–0.85 (Master's), and 0.75–0.91 (PhD). Behavioural Intention (BI) items showed loadings of 0.80–0.88 for males and 0.75–0.85 for females. Age groups recorded 0.74–0.83 (18–24), 0.77–0.86

(25–34), and 0.80–0.90 (35–44); educational loadings were 0.80–0.88 for OND, 0.67–0.84 for HND, 0.79–0.88 for Bachelor's, 0.70–0.89 for Master's, and 0.82–0.92 for PhD holders. Finally, ChatGPT Use Behaviour (UB) items ranged from 0.82 to 0.86 for males and 0.79–0.86 for females, with age loadings of 0.79–0.86 (18–24), 0.80–0.89 (25–34), and 0.81–0.92 (35–44); educationally, loadings were 0.81–0.86 for Bachelor's, 0.80–0.89 for Master's, and 0.84–0.92 for PhD holders.

5.1.2 Average variance extracted

The Average Variance Extracted (AVE) assesses convergent validity by measuring the variance captured by a construct relative to its indicators, with a recommended minimum of 0.50 [23, 25]. Table 2 indicates that for gender subgroups, AVE values range from 0.643 to 0.758 for males and 0.506 to 0.706 for females, satisfying the threshold. For age, the 18–24, 25–34, and 35–44 groups show AVE ranges of 0.531–0.733, 0.570–0.734, and 0.574–0.709, respectively. Similarly, educational subgroups exceed 0.50. These results confirm that all constructs exhibit adequate convergent validity across gender, age, and educational levels.

5.1.3 Composite reliability

Composite reliability (CR) was assessed across demographic subgroups (gender, age, and education level) to evaluate internal consistency. In accordance with Hair et al. (2010), CR values exceeding 0.70 are acceptable, with values above 0.90 indicating high

Table 2 Measurement model metrics for UTAUT2 variables across Gender, Age, and education level subgroups

Metric	Variables	A	B	C	D	E	F	G	H
Average Variance Extracted	PE	0.671	0.619	0.603	0.667	0.681	0.574	0.635	0.789
	EE	0.697	0.570	0.657	0.600	0.678	0.670	0.654	0.697
	SI	0.644	0.506	0.531	0.570	0.646	0.617	0.577	0.568
	FC	0.643	0.616	0.631	0.610	0.637	0.650	0.584	0.681
	HM	0.662	0.611	0.626	0.626	0.687	0.633	0.653	0.700
	HT	0.758	0.706	0.733	0.734	0.709	0.749	0.755	0.730
	BI	0.704	0.643	0.677	0.649	0.740	0.677	0.642	0.799
	UB	0.731	0.686	0.707	0.725	0.658	0.701	0.678	0.791
Composite Reliability	PE	0.891	0.866	0.858	0.889	0.895	0.843	0.874	0.937
	EE	0.873	0.796	0.851	0.817	0.862	0.859	0.849	0.873
	SI	0.844	0.754	0.766	0.799	0.845	0.827	0.803	0.795
	FC	0.878	0.865	0.872	0.861	0.875	0.881	0.846	0.895
	HM	0.907	0.887	0.893	0.893	0.917	0.896	0.904	0.921
	HT	0.926	0.906	0.917	0.917	0.906	0.923	0.925	0.915
	BI	0.877	0.842	0.862	0.847	0.895	0.863	0.842	0.922
	UB	0.891	0.867	0.879	0.888	0.852	0.876	0.863	0.919
Cronbach's Alpha	PE	0.837	0.794	0.781	0.834	0.845	0.751	0.810	0.911
	EE	0.786	0.671	0.751	0.678	0.782	0.756	0.749	0.789
	SI	0.736	0.529	0.642	0.629	0.732	0.714	0.634	0.656
	FC	0.815	0.793	0.806	0.795	0.808	0.821	0.762	0.847
	HM	0.872	0.840	0.850	0.851	0.887	0.856	0.867	0.893
	HT	0.893	0.861	0.879	0.878	0.861	0.888	0.891	0.875
	BI	0.790	0.723	0.763	0.730	0.824	0.762	0.718	0.873
	UB	0.815	0.772	0.793	0.810	0.742	0.787	0.763	0.869

A = Male; B = Female; C = 18 to 24 years; D = 25 to 34 years; E = 35 to 44 years; F = Bachelor's; G = Master's; H = PhD. Values represent Cronbach's Alpha for each variable across the different demographic subgroups. The recommended cut-off for AVE is ≥ 0.50, whereas for Cronbach's alpha and composite reliability is ≥ 0.70 [23, 42] reliability. Table 2 shows that for males, CR values range from 0.873 for Effort Expectancy (EE) to 0.926 for Habit (HT), and for females, from 0.796 (EE) to 0.923 (HT). Although EE values are marginally lower for females, they still meet the minimum threshold. For age groups, CR values range from 0.754 (Social Influence, SI) to 0.917 (HT) for the 18–24 group, from 0.799 (SI) to 0.917 (HT) for the 25–34 group, and from 0.845 (SI) to 0.906 (HT) for the 35–44 group. In terms of education, Bachelor's degree holders show CR values between 0.843 (Performance Expectancy, PE) and 0.904 (HT), Master's degree holders range from 0.846 (Facilitating Conditions, FC) to 0.925 (HT), and PhD holders exhibit values from 0.919 (ChatGPT Use Behaviour, UB) to 0.937 (PE). These results confirm strong internal consistency and reliability across all demographic subgroups.

5.1.4 Cronbach's alpha

Cronbach's alpha was computed for each construct across demographic subgroups (gender, age, and education level) to evaluate scale reliability. Table 2 shows that for males, alpha values ranged from 0.736 (Social Influence, SI) to 0.893 (Habit, HT), exceeding the 0.70 threshold [42]. In contrast, female alpha values ranged from 0.529 (SI) to 0.861 (HT), with SI falling below the acceptable level, suggesting the need for scale refinement for this subgroup. For age groups, individuals aged 18–24 showed alpha values from 0.629 (SI) to 0.879 (Use Behaviour, UB), while the 25–34 group ranged from 0.795 (Facilitating Conditions, FC) to 0.878 (HT). The 35–44 group recorded alpha values from 0.732 (SI) to 0.887 (Hedonic Motivation, HM), all meeting the threshold.

Regarding education, Bachelor's degree respondents reported alpha values between 0.751 (Performance Expectancy, PE) and 0.821 (FC). Master's respondents ranged from 0.718 (Behavioural Intention, BI) to 0.891 (HT), with BI suggesting possible improvement. For PhD holders, alpha values ranged from 0.656 (SI) to 0.893 (HM), again indicating adequate consistency except for SI. Overall, while most constructs demonstrate acceptable reliability, the SI scale for females and PhD respondents warrants further investigation [58].

5.2 Structural model

5.2.1 H1A: performance expectancy → Behavioural intention

Table 3 indicates that performance expectancy (PE) significantly and positively influences behavioral intention (BI) across all demographic subgroups. For males, the effect is stronger ($\beta = 0.176$, $p < .05$) than for females ($\beta = 0.066$, $p < .05$). Among age groups, PE has the strongest effect on participants aged 35–44 years ($\beta = 0.266$, $p < .05$), followed by those aged 18–24 ($\beta = 0.141$, $p < .05$) and 25–34 ($\beta = 0.088$, $p < .05$). In terms of education, the effect is most pronounced for PhD holders ($\beta = 0.196$, $p < .05$), followed by master's ($\beta = 0.182$, $p < .05$) and bachelor's degree holders ($\beta = 0.126$, $p < .05$).

Table 4 further reveals a significant gender difference in the direct effect of PE on BI ($\delta = 0.205$, $p < .05$). While no significant age differences were found between the 18–24 and 25–34 ($\delta = 0.259$, $p > .05$) or the 18–24 and 35–44 groups ($\delta = 0.515$, $p > .05$), a significant difference emerged between the 25–34 and 35–44 groups ($\delta = 0.255$, $p < .05$). Regarding education, no significant differences were detected between bachelor's and master's ($\delta = 5.078$, $p > .05$) or between bachelor's and PhD holders ($\delta = 4.914$, $p > .05$);

Table 3 Path coefficients (β) and p-values for the hypothesized relationships across subgroups

Hypotheses	A		B		C		D		E		F		G		H	
	β	***p***	**β**	***p***	**β**	***p***	**β**	***P***	**β**	***p***	**β**	***p***	**β**	***p***	**β**	***p***
H1A: PE → BI	0.176	0.000	0.066	0.000	0.141	0.000	0.088	0.000	0.266	0.000	0.126	0.000	0.182	0.000	0.196	0.000
H1B: PE → UB	−0.116	0.000	−0.018	0.296	0.052	0.018	−0.127	0.000	−0.214	0.000	0.019	0.344	−0.218	0.000	−0.163	0.000
H2A: EE → BI	−0.036	0.019	0.029	0.149	−0.034	0.157	−0.024	0.224	0.068	0.002	0.143	0.000	−0.066	0.001	−0.193	0.000
H2B: EE → UB	0.013	0.371	0.001	0.947	0.066	0.000	−0.038	0.045	−0.105	0.000	0.021	0.332	−0.091	0.000	0.042	0.041
H3A: SI → BI	−0.039	0.001	0.037	0.041	0.059	0.001	−0.004	0.804	−0.015	0.379	−0.132	0.000	0.098	0.000	0.014	0.465
H3B: SI → UB	−0.059	0.000	0.081	0.000	0.136	0.000	−0.027	0.073	−0.173	0.000	0.131	0.000	−0.153	0.000	−0.094	0.000
H4A: FC → BI	−0.029	0.082	−0.112	0.000	−0.034	0.220	−0.133	0.000	0.050	0.057	−0.218	0.000	−0.043	0.014	0.067	0.014
H4B: FC → UB	0.131	0.000	0.176	0.000	0.064	0.005	0.166	0.000	0.099	0.000	0.185	0.000	0.196	0.000	0.040	0.056
H5A: HM → BI	0.354	0.000	0.325	0.000	0.293	0.000	0.405	0.000	0.182	0.000	0.342	0.000	0.301	0.000	0.422	0.000
H5B: HM → UB	0.292	0.000	0.118	0.000	0.162	0.000	0.282	0.000	0.359	0.000	0.020	0.426	0.316	0.000	0.236	0.000
H6A: HT → BI	0.403	0.000	0.284	0.000	0.297	0.000	0.429	0.000	0.263	0.000	0.401	0.000	0.420	0.000	0.366	0.000
H6B: HT → UB	0.344	0.000	0.251	0.000	0.110	0.000	0.375	0.000	0.475	0.000	0.201	0.000	0.366	0.000	0.473	0.000
H7: BI → UB	0.266	0.000	0.382	0.000	0.457	0.000	0.227	0.000	0.287	0.000	0.439	0.000	0.236	0.000	0.384	0.000

Subgroup labels: A = Male; B = Female; C = 18 to 24 years; D = 25 to 34 years; E = 35 to 44 years; F = Bachelor's; G = Master's; H = PhD. Variable labels: PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; HM = Hedonic Motivation; HT = Habit; BI = Behavioural Intention; UB = ChatGPT Use Behaviour however, a significant difference was observed between master's and PhD holders ($\delta = 0.163$, $p < .05$).

5.2.2 H1B: performance expectancy (PE) → ChatGPT use behaviour (UB)

Performance expectancy had a negative and significant effect on ChatGPT use behaviour for males ($\beta = -0.116$, $p < .05$) and females ($\beta = -0.018$, $p = .296$). Among the age groups, significant negative effects were recorded for those aged 35 to 44 years ($\beta = -0.214$, $p < .05$) and those aged 25 to 34 years ($\beta = -0.127$, $p < .05$). However, the effect was positive and significant for those 18 to 24 years ($\beta = 0.053$, $p < .05$). In terms of education, the effect of PE on UB was positive but insignificant for bachelor's degree holders ($\beta = 0.019$, $p < .05$), while it was negative and statistically significant for master's ($\beta = -0.218$, $p < .05$), and PhD holders ($\beta = -0.163$, $p < .05$).

The significance test presented in Table 4 indicates a significant difference between males and females ($\delta = 0.311$, $p < .05$) in the direct effect of PE on UB. For age groups, no significant differences were observed between 18 and 24 vs. 25–34 years ($\delta = 0.120$, $p > .05$) and 18–24 vs. 35–44 years ($\delta = 0.331$, $p > .05$), but a significant difference was found between the 25–34 and 35–44-year-old groups ($\delta = 0.212$, $p < .05$). Regarding educational levels, no significant differences were noted between Bachelor's and Master's degree holders ($\delta = 5.712$, $p > .05$) or Bachelor's and PhD holders ($\delta = 5.853$, $p > .05$), but a significant difference was detected between Master's and PhD holders ($\delta = 0.141$, $p < .05$).

5.3 H2A: effort expectancy → behavioural intention

Effort expectancy had a negative and significant effect on behavioural intention for males ($\beta = -0.036$, $p < .05$), while it had a positive but insignificant effect for females ($\beta = 0.029$, $p > .05$). Among the age groups, the effect was insignificantly negative for both the 18 to 24 years ($\beta = -0.034$, $p > .05$) and 25 to 34 years ($\beta = -0.024$, $p > .05$) groups, while it was positive and significant for those aged 35 to 44 years ($\beta = 0.068$, $p < .05$). In terms of education, the effect of EE on BI was significant and positive for bachelor's degree holders ($\beta = 0.143$, $p < .05$), while it was significantly negative for master's ($\beta = -0.066$, $p < .05$), and PhD holders ($\beta = -0.193$, $p < .05$).

The significance test in Table 4 shows a significant difference between males and females ($\delta = 0.141$, $p < .05$) in the direct effect of EE on BI. Among age groups, no significant differences were found between 18 and 24 vs. 25–34 years ($\delta = 0.691$, $p > .05$) and 18–24 vs. 35–44 years ($\delta = 0.315$, $p > .05$), while a significant difference was observed between the 25–34 and 35–44-year-old groups ($\delta = 0.376$, $p < .05$) in the direct effect of EE on BI. Regarding educational levels, no significant differences were noted between Bachelor's and Master's degree holders ($\delta = 5.317$, $p > .05$) or Bachelor's and PhD holders ($\delta = 5.517$, $p > .05$); however, a significant difference was identified between Master's and PhD holders ($\delta = 0.200$, $p < .05$).

5.3.1 H2B: effort expectancy → ChatGPT use behaviour

Effort expectancy showed a positive but insignificant effect on ChatGPT use behaviour for males ($\beta = 0.013$, $p > .05$) and females ($\beta = 0.001$, $p > .05$). For the age groups, significant negative effects were recorded for those aged 25 to 34 years ($\beta = -0.038$, $p < .05$) and those aged 35 to 44 years ($\beta = -0.105$, $p < .05$). However, it was positive and significant for those aged 18 to 24 years ($\beta = 0.066$, $p < .05$). In terms of education, the effect of EE on

Table 4 Statistical test of significance in pairwise differences in the multigroup analysis

Hypotheses	A vs. B, *p*-value	C vs. D, *p*-value	C vs. E, *p*-value	D vs. E, *p*-value	F vs. G, *p*-value	F vs. H, *p*-value	G vs. H, *p*-value
H1A: PE → BI	δ = 0.205, *p* = .000	δ = 0.259, *p* = .757	δ = 0.515, *p* = .145	δ = 0.255, *p* = .000	δ = 5.078, *p* = .323	δ = 4.914, *p* = .324	δ = 0.163, *p* = .001
H1B: PE → UB	δ = 0.311, *p* = .000	δ = 0.120, *p* = .080	δ = 0.331, *p* = .119	δ = 0.212, *p* = .000	δ = 5.712, *p* = .367	δ = 5.853, *p* = .360	δ = 0.141, *p* = .035
H2A: EE → BI	δ = 0.141, *p* = .014	δ = 0.691, *p* = .088	δ = 0.315, *p* = .716	δ = 0.376, *p* = .000	δ = 5.317, *p* = .318	δ = 5.517, *p* = .313	δ = 0.200, *p* = .006
H2B: EE → UB	δ = 0.113, *p* = .024	δ = 0.529, *p* = .043	δ = 0.379, *p* = .048	δ = 0.150, *p* = .066	δ = 6.802, *p* = .360	δ = 6.627, *p* = .372	δ = 0.175, *p* = .022
H3A: SI → BI	δ = 0.154, *p* = .002	δ = 0.234, *p* = .033	δ = 0.096, *p* = .088	δ = 0.138, *p* = .002	δ = 1.649, *p* = .300	δ = 1.507, *p* = .312	δ = 0.143, *p* = .001
H3B: SI → UB	δ = 0.262, *p* = .000	δ = 0.323, *p* = .008	δ = 0.465, *p* = .008	δ = 0.142, *p* = .015	δ = 1.612, *p* = .519	δ = 1.742, *p* = .467	δ = 0.130, *p* = .037
H4A: FC → BI	δ = 0.158, *p* = .002	δ = 0.634, *p* = .399	δ = 0.825, *p* = .157	δ = 0.191, *p* = .000	δ = 5.430, *p* = .324	δ = 5.737, *p* = .315	δ = 0.307, *p* = .000
H4B: FC → UB	δ = 0.118, *p* = .011	δ = 0.385, *p* = .051	δ = 0.225, *p* = .058	δ = 0.160, *p* = .001	δ = 7.372, *p* = .376	δ = 7.138, *p* = .395	δ = 0.234, *p* = .000
H5A: HM → BI	δ = 0.025, *p* = .706	δ = 0.340, *p* = .986	δ = 0.954, *p* = .141	δ = 0.615, *p* = .000	δ = 6.192, *p* = .323	δ = 5.943, *p* = .327	δ = 0.250, *p* = .000
H5B: HM → UB	δ = 0.396, *p* = .000	δ = 0.211, *p* = .074	δ = 0.235, *p* = .076	δ = 0.024, *p* = .777	δ = 8.334, *p* = .396	δ = 8.405, *p* = .394	δ = 0.071, *p* = .452
H6A: HT → BI	δ = 0.173, *p* = .000	δ = 0.419, *p* = .060	δ = 0.130, *p* = .384	δ = 0.290, *p* = .000	δ = 0.097, *p* = .203	δ = 0.072, *p* = .308	δ = 0.169, *p* = .000
H6B: HT → UB	δ = 0.147, *p* = .002	δ = 0.490, *p* = .034	δ = 0.598, *p* = .029	δ = 0.108, *p* = .185	δ = 0.674, *p* = .462	δ = 0.478, *p* = .637	δ = 0.196, *p* = .012
H7: BI → UB	δ = 0.011, *p* = .707	δ = 0.043, *p* = .106	δ = 0.002, *p* = .085	δ = 0.041, *p* = .378	δ = 0.839, *p* = .343	δ = 0.729, *p* = .403	δ = 0.110, *p* = .032

δ = pairwise difference; Subgroup labels: A = Male; B = Female; C = 18 to 24 years; D = 25 to 34 years; E = 35 to 44 years; F = Bachelor's; G = Master's; H = PhD

UB was positive but insignificant for bachelor's degree holders (β = 0.021, *p* > .05), while it was significantly positive for PhD (β = 0.042, *p* < .05). However, the effect of EE on UB was significantly negative for master's students (β = −0.091, *p* < .05).

As shown in Table 4, a significant difference was found between males and females (δ = 0.113, *p* < .05) in the direct effect of EE on UB. Significant differences were also observed in the direct of EE on UB between the age groups 18–24 vs. 25–34 years (δ = 0.529, *p* < .05) and 18–24 vs. 35–44 years (δ = 0.379, *p* < .05), but not between the 25–34 and 35–44-year-old groups (δ = 0.150, *p* > .05). For educational levels, no significant differences were detected between Bachelor's and Master's degree holders (δ = 6.802, *p* > .05) or Bachelor's and PhD holders (δ = 6.627, *p* > .05), while a significant difference emerged between Master's and PhD holders (δ = 0.175, *p* < .05).

5.3.2 H3A: social influence → Behavioural intention

Table 3 indicates that Social Influence (SI) has differential effects on Behavioural Intention (BI) across demographic groups. For males, SI negatively and significantly affects BI (β = −0.039, *p* < .05), whereas for females, the effect is positive and significant (β = 0.037, *p* < .05). Among age groups, SI exerts a positive, significant influence on BI for those aged 18–24 (β = 0.059, *p* < .05); however, for individuals aged 25–34 (β = −0.004, *p* > .05) and 35–44 (β = −0.015, *p* = .379), the effect is negative but not statistically significant. In terms of education, SI has a significant negative effect for bachelor's degree holders (β

= −0.132, $p<.05$) and a significant positive effect for master's degree holders (β = 0.098, $p<.05$), while for PhD holders the effect is positive yet insignificant (β = 0.014, $p=.465$).

Table 4 further reveals significant gender differences (δ = 0.154, $p<.05$) in SI's effect on BI. Significant differences also exist between the 18–24 and 25–34 age groups (δ = 0.234, $p<.05$) and between the 25–34 and 35–44 groups (δ = 0.138, $p<.05$), but not between the 18–24 and 35–44 groups (δ = 0.096, $p>.05$). For education, while differences between bachelor's and master's (δ = 1.649, $p>.05$) and bachelor's and PhD holders (δ = 1.507, $p>.05$) are not significant, a significant difference is observed between master's and PhD holders (δ = 0.143, $p<.05$).

5.3.3 H3B: social influence and ChatGPT use behaviour

Table 3 indicates that Social Influence (SI) exerts varying effects on ChatGPT Use Behaviour (UB) across demographic subgroups. For gender, SI has a negative, significant effect for males (β = −0.059, $p<.05$) and a positive, significant effect for females (β = 0.081, $p<.05$). Among age groups, respondents aged 18–24 exhibit a positive, significant effect (β = 0.136, $p<.05$), while the 25–34 group shows a negative, non-significant effect (β = −0.027, $p>.05$) and the 35–44 group demonstrates a negative, significant effect (β = −0.173, $p<.05$). In terms of education, bachelor's degree holders display a positive, significant effect (β = 0.131, $p<.05$), whereas master's (β = −0.153, $p<.05$) and PhD holders (β = −0.094, $p<.05$) experience negative, significant effects.

Table 4 reveals a significant difference between males and females (δ = 0.262, $p<.05$) in the SI–UB relationship. Additionally, significant differences are observed between the 18–24 and 25–34 groups (δ = 0.323, $p<.05$), between 18 and 24 and 35–44 groups (δ = 0.465, $p<.05$), and between the 25–34 and 35–44 groups (δ = 0.142, $p<.05$). For education, while no significant differences exist between bachelor's and master's (δ = 1.612, $p>.05$) or between bachelor's and PhD holders (δ = 1.742, $p>.05$), a significant difference is evident between master's and PhD holders (δ = 0.130, $p<.05$).

5.3.4 H4A: facilitating conditions → behavioural intention

Table 3 indicates that facilitating conditions (FC) significantly influence behavioral intention (BI) across demographic subgroups, albeit with variations. For males, FC's effect on BI was negative but not significant (β = −0.029, $p=.082$), whereas for females it was negative and significant (β = −0.112, $p<.001$). Among age groups, the 25–34-year-olds experienced the strongest negative effect (β = −0.133, $p<.001$), while the 35–44 group showed an insignificant positive effect (β = 0.050, $p>.05$), and the 18–24 group displayed an insignificant negative effect (β = −0.034, $p>.05$). In terms of education, FC exerted a significant negative effect on BI for both bachelor's (β = −0.218, $p<.05$) and master's degree holders (β = −0.530, $p<.05$), but a significant positive effect for PhD holders (β = 0.067, $p<.05$).

Table 4 reveals a significant difference between males and females (δ = 0.158, $p<.05$) regarding FC's effect on BI. While no significant age differences were detected between the 18–24 group and the older groups, a significant difference emerged between the 25–34 and 35–44 groups (δ = 0.191, $p<.05$). Additionally, although bachelor's and master's or PhD holders did not differ significantly, a significant difference was found between master's and PhD holders (δ = 0.307, $p<.05$).

5.3.5 H4B: facilitating conditions → ChatGPT use behaviour

Table 3 indicates that Facilitating Conditions (FC) significantly and positively influence ChatGPT Use Behaviour (UB) across most demographic subgroups. For males, FC's effect on UB is $\beta = 0.131$ ($p < .05$), and for females, $\beta = 0.176$ ($p < .05$). Among age groups, the effect is significant for respondents aged 18–24 ($\beta = 0.064$, $p < .05$), 25–34 ($\beta = 0.166$, $p < .05$), and 35–44 ($\beta = 0.099$, $p < .05$). Regarding education, FC shows the strongest effect among master's degree holders ($\beta = 0.196$, $p < .05$), followed by bachelor's degree holders ($\beta = 0.185$, $p < .05$), while the effect for PhD holders is positive but insignificant ($\beta = 0.040$, $p > .05$).

Table 4 reveals a significant difference between males and females ($\delta = 0.118$, $p < .05$) in the FC–UB relationship. No significant differences are observed between the 18–24 group and older age groups; however, a significant difference exists between respondents aged 25–34 and 35–44 ($\delta = 0.160$, $p < .05$). Regarding education, differences between bachelor's and master's ($\delta = 7.372$, $p > .05$) and between bachelor's and PhD holders ($\delta = 7.138$, $p > .05$) are not significant, but a significant difference is evident between master's and PhD holders ($\delta = 0.234$, $p < .05$).

5.3.6 H5A: hedonic motivation → behavioural intention

Table 3 reveals that Hedonic Motivation (HM) exerts a significant, positive effect on Behavioural Intention (BI) across all demographic subgroups. Specifically, HM's impact on BI is significant for both males ($\beta = 0.354$, $p < .05$) and females ($\beta = 0.325$, $p < .05$). Among age groups, the effect is strongest for those aged 25–34 years ($\beta = 0.405$, $p < .05$), followed by individuals aged 18–24 years ($\beta = 0.293$, $p < .05$) and 35–44 years ($\beta = 0.182$, $p < .05$). Regarding education, HM significantly influences BI for all levels, with the highest effect observed for PhD holders ($\beta = 0.422$, $p < .05$), followed by bachelor's ($\beta = 0.342$, $p < .05$) and master's degree holders ($\beta = 0.301$, $p < .05$).

Table 4 further indicates a significant difference between male and female respondents in the HM–BI relationship ($\delta = 0.143$, $p < .05$). While no significant age differences were found between the 18–24 and 25–34 groups ($\delta = 0.457$, $p > .05$) or between 18 and 24 and 35–44 groups ($\delta = 0.331$, $p > .05$), a significant difference exists between the 25–34 and 35–44 groups ($\delta = 0.198$, $p < .05$). Regarding education, significant differences were observed only between master's and PhD holders ($\delta = 0.289$, $p < .05$).

5.3.7 H5B: hedonic motivation → ChatGPT use behaviour

Table 3 indicates that Human Motivation (HM) significantly influences ChatGPT Use Behaviour (UB) across various subgroups. For gender, HM's effect is positive and significant for males ($\beta = 0.292$, $p < .05$) and females ($\beta = 0.118$, $p < .05$). Among age groups, the strongest effect is observed in the 35–44 years group ($\beta = 0.359$, $p < .05$), followed by the 25–34 years group ($\beta = 0.282$, $p < .05$), and the 18–24 years group ($\beta = 0.162$, $p < .05$). In terms of education, the effect of HM on UB is not significant for bachelor's degree holders ($\beta = 0.020$, $p > .05$), whereas it is positive and significant for master's ($\beta = 0.316$, $p < .05$) and PhD holders ($\beta = 0.236$, $p < .05$).

Table 4 reveals a significant difference between male and female respondents in the HM–UB relationship ($\delta = 0.136$, $p < .05$). While no significant differences were found between respondents aged 18–24 and those aged 25–34 ($\delta = 0.501$, $p > .05$) or between 18 and 24 and 35–44 ($\delta = 0.245$, $p > .05$), a significant difference exists between the 25–34 and 35–44 groups (δ = 0.187, p <.05). Regarding education, there were no significant differences between bachelor's and master's (δ = 7.025, p >.05) or between bachelor's and PhD holders (δ = 7.240, p >.05); however, a significant difference was observed between master's and PhD holders (δ = 0.215, p <.05).

5.3.8 H6A: habit → behavioural intention

Table 3 indicates that Habit (HT) significantly and positively influences Behavioural Intention (BI) across all subgroups. For males, HT's effect on BI is β = 0.403 (p <.05), compared to β = 0.284 (p <.05) for females. Among age groups, the effect is strongest for individuals aged 25–34 years (β = 0.429, p <.001), followed by those aged 18–24 (β = 0.297, p <.05) and 35–44 (β = 0.263, p <.05). Regarding education, the strongest effect is observed for master's degree holders (β = 0.420, p <.05), followed by PhD holders (β = 0.366, p <.05) and bachelor's degree holders (β = 0.401, p <.05).

Table 4 reveals a significant gender difference in the HT–BI relationship (δ = 0.173, p <.05). Among age groups, no significant differences exist between 18 and 24 and 25–34 (δ = 0.419, p >.05) or between 18 and 24 and 35–44 (δ = 0.130, p >.05); however, a significant difference is found between the 25–34 and 35–44 groups (δ = 0.290, p <.05). Regarding education, no significant differences are noted between bachelor's and master's (δ = 0.097, p >.05) or bachelor's and PhD holders (δ = 0.072, p >.05), but a significant difference emerges between master's and PhD holders (δ = 0.169, p <.05).

5.3.9 H6B: habit → ChatGPT use behaviour

Table 3 indicates that Habit (HT) significantly and positively influences ChatGPT Use Behaviour (UB) across all demographic subgroups. For males, HT yields a standardized coefficient of β = 0.344 (p <.05), and for females, β = 0.251 (p <.05). The effect is strongest among individuals aged 35–44 (β = 0.475, p <.05), followed by those aged 25–34 (β = 0.375, p <.05), and weakest among the 18–24 group (β = 0.110, p <.05). In terms of education, PhD holders exhibit the highest impact (β = 0.473, p <.05), followed by master's degree holders (β = 0.366, p <.05) and bachelor's degree holders (β = 0.201, p <.05).

Table 4 further reveals a significant difference between males and females (δ = 0.147, p <.05) regarding the HT–UB relationship. Among age groups, significant differences exist between the 18–24 and 25–34 groups (δ = 0.490, p <.05) and between the 18–24 and 35–44 groups (δ = 0.598, p <.05), whereas the 25–34 and 35–44 groups do not differ significantly (δ = 0.108, p >.05). For education, no significant differences are observed between bachelor's and master's (δ = 0.674, p >.05) or bachelor's and PhD holders (δ = 0.478, p >.05); however, a significant difference is found between master's and PhD holders (δ = 0.196, p <.05).

5.3.10 H7: behavioural intention → ChatGPT use behaviour

Table 3 indicates that Behavioural Intention (BI) significantly and positively influences ChatGPT Use Behaviour (UB) across all demographic subgroups. Specifically, for males, the standardized coefficient is β = 0.266 (p <.05), while for females it is β = 0.382 (p <.05). Among age groups, the effect is strongest for individuals aged 18–24 years (β = 0.457, p <.05), followed by those aged 25–34 years (β = 0.287, p <.05), and weakest for the 35–44 years group (β = 0.227, p <.05). Regarding education, the impact is highest for master's degree holders ($\beta = 0.439$, $p < .05$), then PhD holders ($\beta = 0.384$, $p < .05$), and lowest for bachelor's degree holders ($\beta = 0.236$, $p < .05$).

Table 4 further reveals no significant gender differences ($\delta = 0.011$, $p > .05$) in the BI–UB relationship. Similarly, pairwise comparisons among age groups show no significant differences ($\delta = 0.043$, 0.002, and 0.041; all $p > .05$). For education, no significant differences were observed between bachelor's and master's ($\delta = 0.839$, $p > .05$) or between bachelor's and PhD holders ($\delta = 0.729$, $p > .05$); however, a significant difference emerged between master's and PhD holders ($\delta = 0.110$, $p < .05$).

5.4 Predictive quality of the model

5.4.1 R-squared and adjusted R-Squared

Table 5 presents the variance explained (R^2) in Behavioural Intention (BI) and ChatGPT Use Behaviour (UB) across demographic groups. For BI, the predictors (PE, EE, SI, FC, HM, and HT) accounted for 53.2% of the variance in males ($R^2 = 0.532$), indicating a moderate effect, while for females the variance explained was 29.6% ($R^2 = 0.296$). Among age groups, respondents aged 18–24 showed an R^2 of 0.357, those aged 25–34 had an R^2 of 0.532, and those aged 35–44 exhibited an R^2 of 0.406. In terms of education, bachelor's degree holders demonstrated weak explanatory power ($R^2 = 0.383$), master's degree holders moderate power ($R^2 = 0.522$), and PhD holders the highest ($R^2 = 0.612$). For ChatGPT UB, the predictors (including BI) explained 58.0% of the variance for males ($R^2 = 0.580$) and 55.1% for females ($R^2 = 0.551$). The 18–24 age group had the highest UB variance explained at 62.8% ($R^2 = 0.628$), followed by 25–34-year-olds ($R^2 = 0.567$) and 35–44-year-olds ($R^2 = 0.551$). Educationally, bachelor's degree holders had an R^2 of 0.581, master's degree holders 0.497, while PhD holders showed substantial explanatory power with an R^2 of 0.767. Adjusted R^2 values, which provide a more conservative estimate by accounting for the number of predictors, followed a similar trend. For BI, adjusted R^2 ranged from 0.531 for males to 0.610 for PhD holders, and for UB, from 0.496 in the master's group to 0.766 in the PhD group.

5.4.2 Mean absolute error (MAE)

Table 5 presents the Mean Absolute Error (MAE) and Q^2p values, which indicate the prediction accuracy of the model for Behavioural Intention (BI) and ChatGPT Use Behaviour (UB) across demographic groups. For BI, MAE values ranged from 0.482 to 0.612. Specifically, males reported a moderate error (MAE = 0.514), while females had a higher error (MAE = 0.612). Among age groups, the 18–24 cohort exhibited an MAE of 0.592, the 25–34 group 0.504, and the 35–44 group 0.580. In terms of education, individuals with a Bachelor's degree had an MAE of 0.547, those with a Master's 0.539, and PhD holders recorded the lowest error (MAE = 0.482), suggesting enhanced prediction with higher educational attainment. For UB, MAE values ranged from 0.432 to 0.561. Males had an MAE of 0.510, and females 0.552. The 18–24 and 25–34 groups both registered an MAE of 0.512, whereas the 35–44 group had the highest error (MAE = 0.561). Bachelor's degree holders had an MAE of 0.532, Master's degree holders 0.574, and PhD holders the lowest (MAE = 0.432).

Table 5 Predictive quality assessment of the model

Outcome variables	A		B		C		D		E		F		G		H	
	R^2	***p***	***R^2***	***p***	***R^2***	***p***	***R^2***	***p***	***R^2***	***p***	***R^2***	***p***	***R^2***	***p***	***R^2***	***p***
BI	0.532	0.000	0.296	0.000	0.357	0.000	0.532	0.000	0.406	0.000	0.383	0.000	0.522	0.000	0.612	0.000
UB	0.580	0.000	0.551	0.000	0.628	0.000	0.567	0.000	0.551	0.000	0.581	0.000	0.497	0.000	0.767	0.000
	Adj. R^2	p	Adj. R^2	p	Adj. R^2	p	Adj. R^2	p	Adj. R^2	p	Adj. R^2	p	Adj. R^2	p	Adj. R^2	p
BI	0.531	0.000	0.295	0.000	0.355	0.000	0.532	0.000	0.404	0.000	0.382	0.000	0.521	0.000	0.610	0.000
UB	0.579	0.000	0.550	0.000	0.627	0.000	0.566	0.000	0.549	0.000	0.580	0.000	0.496	0.000	0.766	0.000
	MAE	Q^2_p	MAE	Q^2_p	MAE	Q^2_p	MAE	Q^2_p	MAE	Q^2_p	MAE	Q^2_p	MAE	Q^2_p	MAE	Q^2_p
BI	0.514	0.530	0.612	0.293	0.592	0.352	0.504	0.530	0.580	0.401	0.547	0.379	0.539	0.519	0.482	0.608
UB	0.510	0.545	0.552	0.445	0.512	0.490	0.512	0.540	0.561	0.498	0.532	0.458	0.574	0.467	0.432	0.707
Paths	F^2	p	F^2	p	F^2	p	F^2	p	F^2	p	F^2	p	F^2	p	F^2	p
PE → BI	0.028	0.000	0.004	0.067	0.015	0.006	0.009	0.009	0.063	0.000	0.011	0.032	0.036	0.000	0.049	0.000
PE → UB	0.013	0.001	0.000	0.679	0.003	0.280	0.019	0.001	0.050	0.000	0.000	0.645	0.047	0.000	0.054	0.000
EE → BI	0.001	0.255	0.001	0.502	0.001	0.443	0.001	0.618	0.004	0.133	0.016	0.000	0.004	0.111	0.043	0.000
EE → UB	0.000	0.767	0.000	0.998	0.006	0.119	0.002	0.285	0.012	0.033	0.001	0.695	0.007	0.069	0.003	0.288
SI → BI	0.002	0.109	0.002	0.333	0.004	0.174	0.000	0.964	0.000	0.744	0.020	0.004	0.016	0.002	0.000	0.777
SI → UB	0.006	0.025	0.012	0.011	0.037	0.000	0.001	0.397	0.052	0.000	0.028	0.000	0.037	0.001	0.027	0.013
FC → BI	0.001	0.433	0.011	0.002	0.001	0.566	0.024	0.000	0.002	0.399	0.027	0.000	0.003	0.211	0.006	0.211
FC → UB	0.019	0.000	0.043	0.000	0.004	0.187	0.039	0.000	0.013	0.026	0.029	0.000	0.051	0.000	0.004	0.381
HM → BI	0.105	0.000	0.066	0.000	0.041	0.000	0.126	0.000	0.024	0.004	0.058	0.000	0.086	0.000	0.143	0.000
HM → UB	0.072	0.000	0.013	0.006	0.021	0.001	0.059	0.000	0.119	0.000	0.000	0.781	0.083	0.000	0.065	0.000
HT → BI	0.222	0.000	0.069	0.000	0.088	0.000	0.210	0.000	0.077	0.000	0.157	0.000	0.210	0.000	0.198	0.000
HT → UB	0.147	0.000	0.079	0.000	0.019	0.002	0.142	0.000	0.307	0.000	0.050	0.000	0.125	0.000	0.459	0.000
BI → UB	0.079	0.000	0.229	0.000	0.361	0.000	0.055	0.000	0.109	0.000	0.283	0.000	0.053	0.000	0.246	0.000

R^2 = Coefficient of determination; Adj, R^2 = Adjusted coefficient of determination; MAE = Mean Absolute Error; Q^2_p = Measure of the predictive power; F^2 = Effect size; p = probability value

5.4.3 Q-squared predict

Table 5 presents the Q^2p values, indicating the model's predictive relevance for Behavioural Intention (BI) and ChatGPT Use Behaviour (UB) across demographic subgroups. For BI, Q^2p ranged from 0.293 to 0.530. The model performed best for males (Q^2p =.530) and the 25–34 age group (Q^2p =.530), while females exhibited a lower value (Q^2p =.293). Respondents aged 18–24 and 35–44 recorded Q^2p values of 0.352 and 0.401, respectively. In terms of education, Bachelor's degree holders had a Q^2p of 0.379, Master's degree holders 0.519, and PhD holders the highest at 0.608. For UB, Q^2p values ranged from 0.445 to 0.707. Males achieved a Q^2p of 0.545, whereas females recorded 0.445. Age-wise, the 18–24 group had a Q^2p of 0.512, the 25–34 group 0.540, and the 35–44 group 0.498. Regarding educational qualifications, Bachelor's and Master's degree holders showed Q^2p values of 0.458 and 0.467, respectively, while PhD holders demonstrated the highest predictive power with a Q^2p of 0.707.

6 Discussion

6.1 Performance expectancy (PE)

Performance expectancy was confirmed to be a key factor influencing students' intentions. The findings indicate that students generally recognise the potential benefits of ChatGPT for improving efficiency and quality in academic tasks, aligning with theoretical expectations that perceived usefulness strongly motivates technology adoption.

The findings revealed that male students and older students expressed higher behavioural intention related to performance expectancy than their female and younger counterparts. This suggests that, within the Nigerian higher education context, these groups may place greater value on tools that can enhance productivity and academic output, potentially due to more intensive academic responsibilities or career-related pressures. Doctoral and master's students also reported stronger behavioural intention, indicating that advanced academic levels amplify the perceived relevance of ChatGPT for complex research and writing tasks. These patterns are consistent with prior studies suggesting that academic maturity and role-related demands influence technology adoption decisions [55, 60].

While behavioural intention was positively associated with performance expectancy across all groups, actual use behaviour followed a different trend. Younger students translated their perception of usefulness into greater use, whereas older students and those at advanced academic levels displayed lower adoption despite recognising the benefits. This divergence aligns with UTAUT2, which distinguishes between intention and actual use, and may reflect practical or situational barriers such as workload, digital familiarity, or the perceived effort required to integrate ChatGPT into complex academic tasks. The results suggest that recognising a tool as beneficial does not automatically lead to usage, particularly for students with greater experience or different academic routines.

These findings extend previous research by demonstrating how demographic characteristics moderate the influence of performance expectancy on both intention and behaviour in an African higher education setting. They indicate that interventions designed to encourage ChatGPT adoption should consider differences in gender, age, and academic level. For example, training and guidance tailored for older students and advanced degree holders may help translate perceived benefits into actual usage. For policy makers and institutional leaders, the findings highlight the importance of supporting academic technologies in ways that account for varying student profiles, ensuring equitable access and integration into academic workflows.

6.2 Effort expectancy (EE)

Effort expectancy was found to have varied effects depending on student characteristics, revealing patterns that extend current understanding of technology adoption in African higher education. For behavioural intention, effort expectancy had a negative influence among male students, while female students reported a positive but limited effect. This finding suggests that males may perceive ChatGPT as requiring additional effort or adjustment, which could reduce their intention to engage with the tool, whereas females, despite recognising potential effort demands, may be more receptive when guided or supported in using the platform. These outcomes align with UTAUT2 expectations, where gender can moderate the perceived ease of use, affecting adoption behaviours [30, 60].

Age also moderated the influence of effort expectancy on behavioural intention. Younger and middle-aged students exhibited minimal influence, while older students demonstrated a positive effect. This pattern indicates that older students may appreciate structured, easy-to-navigate technologies that reduce cognitive load and improve efficiency in completing academic tasks. In contrast, younger students, who are generally more digitally fluent, may perceive minimal barriers and thus exhibit less variation in their behavioural intention based on perceived effort. The finding is consistent with studies suggesting that age can influence the salience of ease of use in technology adoption [55].

Academic level further influenced the relationship between effort expectancy and intention. Bachelor's degree students responded positively to the ease of use of ChatGPT, whereas master's and doctoral students reported negative associations. This trend may reflect the greater complexity of tasks undertaken by advanced students, who may require more than ease of use alone to integrate ChatGPT effectively into research or academic writing. The results suggest that prior experience, task demands, and expectations of academic performance can moderate how perceived effort influences adoption.

The influence of effort expectancy on actual use behaviour revealed additional complexity. Younger students translated perceived ease of use into higher engagement with ChatGPT, consistent with their familiarity with digital technologies. Conversely, older students and master's students showed reduced use despite recognising the platform's ease of use, indicating that intention alone may not suffice to drive adoption without addressing contextual factors such as workload, time constraints, or familiarity with AI tools. Doctoral students, however, demonstrated positive use behaviour, suggesting that when effort is manageable and aligned with high-value academic tasks, adoption improves.

These findings have practical implications for Nigerian higher education. Institutions aiming to promote ChatGPT adoption should provide structured training, particularly for older students and those at advanced academic levels, to translate perceived ease of use into sustained engagement. Designers and administrators of academic technologies should also consider tailoring interfaces and support to match the varying experience levels and task requirements of different student groups.

6.3 Social influence (SI)

Social influence, defined in UTAUT2 as the degree to which individuals perceive that important others expect them to use a technology, was found to exert varying effects depending on student characteristics. For behavioural intention, female students responded positively to social influence, whereas male students reported a negative response. This pattern suggests that females may be more receptive to peer recommendations and institutional guidance when adopting new technologies, while males may place less weight on social expectations, potentially relying on personal judgement or prior experience. These findings align with UTAUT2 assumptions, where gender moderates how social influence shapes technology adoption [30, 60].

Age also affected the relationship between social influence and behavioural intention. Younger students, particularly those aged 18 to 24, were positively influenced by social cues, whereas older students displayed weaker or negative responses. This result suggests that younger students may rely more on peers, instructors, and institutional messaging when forming intentions to use ChatGPT, while older students may prioritise individual assessment of the technology's relevance and utility. These outcomes extend prior research indicating that age influences responsiveness to social pressure in technology adoption [55].

Academic level further moderated the effects of social influence. Bachelor's degree students reported negative reactions, while master's students were positively influenced, and doctoral students showed limited response. These differences may reflect variations in academic responsibilities and autonomy. Undergraduate students may feel constrained by peer expectations but may lack the experience to convert social pressure into meaningful engagement, whereas postgraduate students, especially at the master's level, may be better positioned to integrate social guidance into intentional technology use.

The influence of social influence on actual use behaviour revealed additional patterns. Female students and younger respondents were more likely to translate social cues into active engagement with ChatGPT. In contrast, male students and older users were less responsive, with some exhibiting reduced use despite positive behavioural intention. Among academic levels, bachelor's students responded positively in terms of use, whereas master's and doctoral students were negatively influenced. These findings suggest that social influence alone may be insufficient to drive sustained technology use among advanced students unless it aligns with perceived value and academic needs.

In the Nigerian higher education setting, these findings carry important practical implications. Institutional initiatives aimed at promoting ChatGPT adoption should emphasise peer-led training, mentoring, and collaborative learning approaches for younger and female students, while providing autonomy-supporting strategies for older and postgraduate students. Academic designers and policymakers should consider how social cues can be structured to encourage adoption without creating resistance among students less influenced by peers.

6.4 Facilitating conditions (FC)

The findings indicate that the influence of facilitating conditions differs between intention and actual use, revealing important implications for promoting AI adoption in Nigerian higher education. For behavioural intention, female students and those aged 25 to 34 were less likely to form strong intentions to use ChatGPT even when facilitating conditions were present. This suggests that mere availability of resources and support may not always translate into a willingness to adopt technology, particularly among students who may perceive the system as complex or who require additional guidance to recognise its relevance. In contrast, doctoral students demonstrated positive behavioural intention when facilitating conditions were strong, indicating that higher-level students may be better able to leverage available support for deliberate technology adoption. These outcomes align with UTAUT2 predictions, which indicate that facilitating conditions interact with user characteristics to influence intention [18, 60].

When examining actual use behaviour, facilitating conditions consistently promoted engagement with ChatGPT across most demographic groups. Both undergraduate and master's students benefited from accessible technical and institutional support, translating intention into regular use. This finding is consistent with prior studies that emphasise the role of facilitating conditions in enabling practical adoption even when initial intention is low [10, 38]. The positive effect on actual use suggests that students may be more responsive to concrete support measures, such as training, access to devices, and institutional guidance, than to social or motivational cues alone.

The contrasting effects on intention and use highlight the complexity of technology adoption in Nigerian higher education. While students may acknowledge the availability of support, other factors such as perceived system difficulty, self-confidence in using AI tools, or competing academic responsibilities may limit their initial willingness to engage with ChatGPT. Over time, however, accessible support appears to facilitate integration into learning routines, indicating that consistent and practical assistance is crucial for sustaining use.

From a practical perspective, the findings suggest that universities and policymakers should prioritise the provision of comprehensive technical support, training programmes, and user guidance to encourage adoption. Tailored strategies may be needed for different groups; for instance, female students and mid-aged undergraduates might benefit from hands-on workshops or mentoring programmes that bridge the gap between available resources and personal confidence in using ChatGPT. Meanwhile, advanced students such as doctoral candidates may require less direct intervention but still benefit from structured access to institutional resources.

6.5 Hedonic motivation (HM)

The findings indicate that intrinsic enjoyment is a strong driver of both the intention to adopt and actual engagement with ChatGPT, reinforcing its importance alongside utilitarian or performance-based factors. For behavioural intention, hedonic motivation was significant across gender, age, and educational levels, with the strongest effect observed among students aged 25 to 34 and doctoral students. This pattern suggests that mid-aged and more academically advanced students may value the stimulating and engaging aspects of ChatGPT, which supports their motivation to adopt the tool. These findings are consistent with the extended UTAUT2 model, which identifies hedonic motivation as a direct predictor of behavioural intention, particularly when moderated by age and experience [46, 60]. The result also aligns with previous studies indicating that enjoyment influences technology adoption, particularly in educational settings [10, 24, 38].

In terms of actual use, hedonic motivation maintained a positive influence across most subgroups, with the strongest effects among respondents aged 35 to 44 and postgraduate students. This finding indicates that intrinsic engagement translates into actual application, particularly for students who are likely to integrate ChatGPT into their routine academic activities. Interestingly, bachelor's degree students did not show a significant effect of hedonic motivation on use behaviour, suggesting that younger undergraduates may require additional guidance or structured incentives to convert enjoyment into sustained application. This observation extends prior research by highlighting that hedonic factors may operate differently across academic levels, reflecting variations in digital literacy, academic maturity, and perceived utility of AI tools (Nikolopoulou et al., 2020; [48].

Gender differences were also observed, with males generally showing stronger relationships between hedonic motivation and both intention and use compared to females. These patterns suggest that male students may be more responsive to the entertaining and engaging aspects of technology, consistent with earlier findings that gender moderates hedonic motivation effects in technology adoption [30, 52]. The observed age effects, where older students translated motivation into actual use more effectively, align with prior evidence that experience and academic maturity can amplify the influence of intrinsic motivators [24, 38].

From a practical perspective, these findings suggest that Nigerian higher education institutions should design strategies that enhance the pleasurable aspects of ChatGPT to promote adoption and sustained use. This could include gamified learning exercises, interactive academic applications, and advanced features tailored to postgraduate students. Undergraduate students may benefit from structured onboarding and guidance that facilitates enjoyable engagement while promoting consistent use.

6.6 Habit (HT)

The study found that habit is a strong predictor of both behavioural intention and actual use of ChatGPT among Nigerian higher education students. Habit, understood as repeated and regular engagement with a technology, positively influences the formation of intention to use the tool as well as its sustained application in academic activities. These findings align with theoretical expectations in UTAUT2, which propose that habitual behaviour facilitates the transition from initial adoption to continued usage, reinforcing students' engagement with digital learning technologies [10, 38, 60].

Analysis across demographic groups revealed that habit had the strongest influence on behavioural intention among students aged 25 to 34 and those with master's degrees. This suggests that students in these categories may encounter greater academic pressures or opportunities that encourage routine use of ChatGPT, potentially integrating it into daily study or research activities. In contrast, younger undergraduates and PhD holders exhibited comparatively lower effects on behavioural intention, indicating that habitual adoption may depend on the combination of academic responsibilities, prior digital experience, and availability of time for repeated engagement. These findings extend prior research by demonstrating that age and academic level moderate the effect of habitual behaviour on technology adoption and sustained use.

Gender differences were also observed, with males showing slightly higher influence of habit on both intention and actual use compared to females. This pattern resonates with previous studies suggesting that males may be more inclined to develop consistent usage routines once initial engagement has occurred [30, 52]. Additionally, the effect of habit on actual use was particularly strong among older students (35–44) and PhD holders, indicating that once habitual routines are established, these groups are more likely to consistently utilise the technology to support complex academic tasks.

From a practical perspective, the findings suggest that Nigerian universities should promote repeated and structured use of ChatGPT to reinforce habitual engagement. Interventions may include embedding ChatGPT-based activities into coursework, providing exercises that encourage regular interaction, and creating reminders to sustain usage patterns. By fostering habitual use, institutions can enhance students' productivity, engagement, and familiarity with AI tools, particularly for postgraduate students who face more intensive learning demands.

6.7 Behavioral intention (BI)

The study confirms that behavioral intention is a key determinant of actual ChatGPT use among Nigerian higher education students. Students who form a deliberate plan to use ChatGPT are more likely to translate this intention into consistent academic practice. This outcome aligns with UTAUT theory, which emphasizes that intention serves as a proximal predictor of technology adoption [7, 59]. The findings suggest that fostering a strong, positive intention to engage with ChatGPT is essential for ensuring its effective integration into educational routines.

Analysis across demographic groups reveals that behavioral intention has the greatest influence on actual use among younger students aged 18–24 and among master's degree holders. This pattern may reflect a combination of higher digital fluency among younger users and the greater academic demands faced by postgraduate students, who may actively seek tools that enhance efficiency and learning outcomes. In contrast, the effect of behavioral intention is comparatively weaker among older students and undergraduates, suggesting that habit formation, prior exposure to technology, or perceived utility may modulate the strength of intention in these groups. These differences extend previous research by demonstrating that demographic characteristics can influence how strongly intention translates into use behaviour, underscoring the importance of targeting interventions to specific student segments [10, 38].

Gender comparisons indicate that although females show slightly higher coefficients linking intention to use, the differences between males and females are not statistically significant. This suggests that the motivational force of intention operates similarly across gender groups, supporting the theoretical expectation that intention should universally predict adoption regardless of gender [60]. However, the significant difference observed between master's and PhD holders implies that academic level may moderate the intention–use relationship, possibly reflecting differences in learning objectives, workload, and the integration of digital tools into research practices.

The implications of these findings for Nigerian higher education are considerable. Institutions should design interventions that explicitly strengthen students' intention to use ChatGPT, such as orientation sessions, guided exercises, and instructional modules that demonstrate the practical benefits of AI tools in academic work. Encouraging deliberate planning around the use of ChatGPT could increase adoption rates, particularly among undergraduates who may require structured support to form consistent usage patterns.

7 Conclusion

This study indicates that factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit are associated with students' behavioral intention to use ChatGPT and their actual use of the tool. In the Nigerian higher education context, these associations vary across different student groups. For example, some groups show stronger links to perceived benefits, while others are more influenced by ease of use or available support. While the study was conducted in Nigeria, the observed patterns may offer insights relevant to other educational settings, with caution due to contextual differences. Educators and policymakers can consider these associations when developing digital learning environments that address the varying needs of student groups. Institutions may use the findings to inform training programs, support systems, and user interfaces that encourage effective engagement with digital tools like ChatGPT. Overall, the study provides evidence that understanding the differing influences on technology use can help shape strategies to enhance educational technology adoption, while recognizing the limits of causal interpretation.

7.1 Limitations and suggestions

This study has several limitations. First, data were self-reported, which may introduce social desirability or recall bias. Future research could complement self-reports with observational or system-tracked usage data to improve accuracy. Second, the online distribution of the questionnaire may have resulted in non-response or selection bias, potentially affecting the representativeness of the sample. Subsequent studies should consider multiple recruitment channels and stratified sampling to address this issue. Third, while this research examined key demographic factors, other potential moderators and mediators such as socioeconomic status, institutional resources, or prior digital literacy were not assessed. Future studies could incorporate these variables to provide a more comprehensive understanding of factors influencing ChatGPT adoption.

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On behalf of all authors, the corresponding author states that she has read the journal policies and she is submitting the manuscript in accordance with the journal policies.

Author contributions
1. **Ibrahim Abba Mohammed** : Conceptualization, writing draft, data collection, technical support, editing and approval2. **Valentine Joseph Owan: ** Conceptualization, methodology, data collection, data analysis, visualisation, editing and approval3. **Glory Thomas** : Writing draft, Data collection and project administration4. **David Francis Ekpoto** : Data collection, supervision and approval.

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Data availability
The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The study was conducted in accordance with the standards of the Nigerian national code of research ethics (https://www.nhrec.net/nhrec? NCHRE_July%2007.pdf) Ethical approval was waived in the study by Nigerian National Health Research Ethics Committee (NHREC) based on its guidelines providing exemption to studies in educational settings involving normal educational practices which is in line with Federal Ministry of Health [22]. Informed written consents to participate in the study were obtained from all individual participants as respondents were assured of confidentiality of their identity and the respondents voluntarily participated in the study.

Consent for publication

Informed written consents to publish the result of the article were obtained from all individual participants and the identities of respondents were not disclosed in the study.

Competing interests

The authors declare no competing interests.

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