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Globalising higher education in Africa through artificial intelligence: student acceptance of ChatGPT in an open distance and e-learning context

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Introduction: Higher education is increasingly globalised through digital technologies, Open Distance Learning, e-Learning, and emerging generative AI. In the absence of research examining the acceptance and use of ChatGPT by students in an Open Distance and e-Learning higher education setting, this study evaluated a UTAUT2 model comprising seven standard predictors and Personal Innovativeness, as well as moderating variables age, gender, work status, and year of study.
Methods: Data collected from 294 students at the largest distance education institution in Africa were analysed using partial least squares structural equation modelling.
Results: Four relationships with Behavioural Intention were significant, with Habit emerging as the strongest predictor, followed by Facilitating Conditions, Personal Innovativeness, and Performance Expectancy. Effort Expectancy was found to be negatively associated with Behavioural Intention. Social Influence and Hedonic Motivation were not significantly associated with Behavioural Intention. For Use Behaviour, Habit was once again the strongest predictor, followed by Facilitating Conditions, with Behavioural Intention negatively associated. Neither Social Influence nor Hedonic Motivation returned a significant relationship with Behavioural Intention. The interaction between Year and Hedonic Motivation was the only significant moderator of Behavioural Intention.
Discussion: As the first UTAUT2 study on the intention and actual use of ChatGPT in an ODeL environment, this study not only offers new insights into ChatGPT use but also leaves ample scope for further research.

KEYWORDS
ChatGPT, globalisation, open distance e-learning, PLS-SEM, UTAUT2

Introduction

Higher education is increasingly globalised through digital technologies, cross-border student participation, and technology-enabled educational provision. In sub-Saharan Africa, this creates opportunities for universities to improve knowledge production, build institutional capacity and strengthen international collaboration, but it also brings challenges such as inequality, limited resources, policy dependence, skills shortages, cultural differences and unequal international relationships (Dzvimbo and Moloi, 2013; Moshtari and Safarpour, 2024) For such reasons Oparinde et al. (2022) argue that internationalisation should be part of teaching, research and other university activities, with attention to diversity, inclusion and local relevance.

Within this rapidly changing digitally mediated higher education environment, the emergence of generative artificial intelligence (AI) represents a further development with potentially significant implications for the globalisation of higher education. At the institutional level, educators have leveraged AI for diverse purposes, including augmenting learning experiences through dynamic feedback (Foroughi et al., 2019), while learners are increasingly adopting it to improve their performance on assignments (Bayaga, 2025). However, the ability of an AI tool such as ChatGPT to generate "human-like" answers and sophisticated essay-style responses has prompted alarm across educational institutions (Leaver and Srdarov, 2023). This unethical use by students (see Crawford et al., 2023; Gamage et al., 2023) has not only led to the development and/or incorporation of AI detection tools, but also to new strategies to bypass these tools (Odri and Yoon, 2023). It is therefore not surprising that researchers have increasingly called for new, relevant AI institutional policies (Lo, 2023).

Research problem

Recent evidence from South African universities shows that digital learning is becoming important for sustainable internationalisation (Oloba, 2026). Here, open distance electronic learning (ODeL) provides an important mechanism for extending access beyond geographical boundaries. Internationally, AI use and its acceptance in higher educational institutions (HEI) have been investigated by several authors (Duong et al., 2023; Firaina and Sulisworo, 2023; Habibi et al., 2023; Romero-Rodríguez et al., 2023; Strzelecki, 2023; Zou and Huang, 2023). However, there is no evidence in the literature that research has been conducted on UTAUT2 factors influencing students' acceptance and use of ChatGPT at an open distance e-learning (ODeL) institution, either internationally or in sub-Saharan Africa. In recent research conducted at a residential higher education institution, Strzelecki (2024) used the well-established "Unified Theory of Acceptance and Use of Technology" (UTAUT2, Venkatesh et al., 2012) framework to address a gap in the literature regarding students' acceptance and use of ChatGPT. Nine out of 10 hypotheses tested were confirmed by the model he used.

The first purpose of this study is to replicate the Strzelecki research, including the model, hypotheses, and the UTAUT2 survey he used, in an ODeL setting, which is recognised as the largest distance education institution in Africa and one of the world's leading mega-universities. This study extends existing research by examining the phenomenon within a novel research context that differs from those investigated in previous studies. In 2025, 380,000 students from across the world, over 80% of whom are from historically disadvantaged (HD) groups, were registered at the institution. Its geographically dispersed student population and digitally mediated educational model provide a particularly relevant context for examining how emerging technologies may contribute to the globalisation of African higher education. Most students are South African citizens, and the challenges HD populations still experience 32 years after democracy are well documented in both the public press and research. For example, recent research by Mdlungu (2026) highlights the persistent challenges faced by HD South African ODeL students. These include a lack of family support, motivation, and institutional care. Conversely, failure is often linked to time poverty, digital exclusion, emotional fatigue, limited feedback, socio-economic hardship, and support systems that do not fully recognise the realities of employed adult learners. To these, we can add alienation, financial difficulties, a lack of readiness, racial background, language problems, and a curriculum that reflects colonial legacies, which are some of the causes that lead to student dropout (Cele et al., 2025). Such challenges are not limited to South Africa only. A recent systematic review of the literature on the challenges of e-learning implementation in sub-Saharan countries (van der Merwe et al., 2023) revealed that challenges identified before 2016 to remain in place.

Most students (around 80%) work full-time while studying part-time. Part-time studies require concentration, motivation, and discipline (Merino et al., 2019). Given time constraints, maintaining an acceptable work-life-study balance may well increase the temptation to use generative AI inappropriately during assessment activities. In addition, at the time of this research, there was no clear institutional AI use policy. Despite all work being automatically submitted to an AI-detection tool which attempts to identify the use of tools that generate and/or humanise AI-generated text, lecturer reports point to AI-assisted assessment completion having become increasingly common—especially in formative and portfolio-based approaches.

The second purpose of this research is to identify associations between various UTAUT2 predictors and ODeL students' behavioural intention to accept and use ChatGPT. UTAUT2 was selected not only because it remains the most extensively validated framework for explaining technology acceptance behaviour, but it has consistently demonstrated strong predictive capability in studies of educational technologies and generative AI.

The results will be of interest not only to an ODeL institution but, in line with Strzelecki (2024), also allow educators to reconsider or even redesign the formal use of AI-driven assessment to improve learning. This study is expected to contribute to the literature in three ways. First, it extends UTAUT2 to an under-researched ODeL context. Second, it provides evidence from the largest ODeL institution in Africa, thereby informing us how an African university can participate in global higher education. Third, it offers practical insights for ODeL universities seeking to develop evidence-based AI governance and assessment policies. Fourth, the study provides empirical evidence to inform the development of digitally enabled, contextually responsive strategies for globalising African higher education.

Literature review and hypotheses development

Evolving from academic concepts in the 1950s, AI has driven a technological revolution. Tobin et al. (2020) quotes research that categorised its development in four phases of five years each: Internet AI (recommender systems), Business AI (fraud detection, financial forecasting), Perception AI (smart devices), and Autonomous AI (new hardware applications, such as self-driving cars). Its rise has also been explained by breakthroughs in machine learning and deep learning, including natural

language processing and real-world applications (Borrellas and Unceta, 2021; Padmaja et al., 2024), algorithms and big data (Helm et al., 2020).

Recent developments in the AI field have led to an explosion of generative AI tools, which are capable of generating novel and realistic content based on basic user prompts (Banh and Strobel, 2023). Some examples include text generation via ChatGPT, Gemini, and Claude; image generation via Midjourney and DALL-E 3; and specialised coding support from GitHub Copilot. It is therefore not surprising to read in a (UNCTAD (UN Trade and Development), 2025) report that the global AI market is projected to grow from $189 billion in 2023 to $4.8 trillion in 2033. This acceleration has also led to an increase in research publications, as is evident in recent reviews of published AI research (Kühl et al., 2022; Sengar et al., 2025).

Meta-analytic evidence and systematic reviews have shown that AI use has positive to moderate effects on HEI students' learning performance (Li et al., 2018; Wu et al., 2026), supports learner-centred education at scale (Garzón et al., 2025; Jiali et al., 2024), enhances student engagement and motivation (Long et al., 2026), and expands access to on-demand academic support (Klimova and Pikhart, 2025).

Further research reports that generative AI tools offer substantial benefits for student learning and instructional practice when pedagogically integrated. Wang and Fan (2025) and Wu et al. (2026) provide evidence that AI use has a moderate-to-large positive effect on students' learning performance, learning perceptions, and higher-order thinking skills, particularly in problem-based, scaffolded, and inquiry-oriented learning environments. Reasons for these benefits include AI's capacity to provide immediate feedback, clarify complex concepts, and support iterative learning, which enable students to regulate their learning and become more productive. Systematic reviews by Merino-Campos (2025) and Garzón et al. (2025) found that AI-driven personalised and adaptive learning systems improve student engagement and motivation by tailoring instructional content, pacing, and feedback to individual learners' needs. Tools such as chatbots have been shown to foster more interactive and responsive learning environments, thereby increasing affective, behavioural, and cognitive engagement (Tran et al., 2025; Dempere et al., 2023). There are institutional and instructional benefits, too. AlBlooshi (2026) mentions reduced administrative burden, enhanced feedback efficiency, and greater instructional flexibility, allowing educators to devote more time to higher-value teaching and mentoring activities.

There is, however, evidence of a pronounced lack of awareness as well as apprehension towards AI (Barrett et al., 2025). In a systematic review of the literature, Celik et al. (2024) identified four specific challenges of AI-based tools, namely accuracy of assessment, challenges in the provision of personalised learning content, autonomy of decision to use AI, and the number of data modalities. To these, AlBlooshi (2026) adds issues such as a need for training, academic integrity, the need to redesign assessments, cognitive offloading and a multitude of ethical concerns.

What remains clear is that the use of ChatGPT in higher education is here to stay and that its use by faculty and students will require ongoing monitoring and review. However, AI adoption should not be viewed solely as an issue of individual technology acceptance; it is also an institutional and systemic issue linked to the sustainability and inclusiveness of globalised higher education (Moshtari and Safarpour, 2024; Oloba, 2026).

In ODeL, the use of technology is embedded in routine academic activities rather than being an optional supplement to face-to-face learning. Given the greater transactional distance, repeated, necessary and regular interaction with digital learning platforms may thus strengthen the habit component of technology acceptance. Zheng et al. (2025) found habit to be the strongest predictor of behavioural intention to use e-learning, while facilitating conditions were also strongly associated with behavioural intention, the latter suggesting that ODeL extends beyond convenience: technological and institutional support may become prerequisites for meaningful participation in the educational process. In a study across four South African residential universities, Terblanche et al. (2023) found that performance expectancy, social influence, facilitating conditions and habit significantly influence behavioural intention to use e-learning applications. Likewise, especially in the South African context of disparities, ODeL students can experience technology difficulties. Mesuwini (2024) reported that South African distance-learning students struggle with shortages of smartphones/laptops, insufficient data, poor connectivity, and inadequate communication from tutors, which limits their participation in educational processes. Outside these technical challenges, and also in an ODeL setting, Chimbo et al. (2023) identified a range of challenges related to the student experience, ranging from a lack of communication, online discussion, and interaction linked to teaching presence, cognitive challenges such as complex modules, and social challenges, which include a lack of online support, virtual interaction, and online participation by teachers-to-students and student-to-peers.

Finally, while online students may perceive technology as useful, they may also consider whether using it is academically acceptable, whether it could expose them to allegations of misconduct, and whether institutional policies permit its use (Nwokocha and Morkel, 2025). In conclusion, while UTAUT2 explains relationships in technology acceptance, an ODeL environment provides contextual conditions that may shape how those relationships operate.

Theoretical framework

Three theories contribute progressively to the current research: Transactional Distance Theory, Self-Regulated Learning Theory, and Technology Adoption Theory.

The Theory of Transactional Distance (Moore, 1997) conceptualises the psychological and pedagogical distance between learner and educator through three elements: structure, dialogue, and learner autonomy. Here, the ODeL student may have a higher intention if ChatGPT is perceived as helping to overcome rigid or complex course structures (structure), compensating for limited dialogue, and managing their own learning (autonomy).

Since ODeL places greater demands on students to independently plan, monitor, and evaluate their learning, the Regulated Learning (SRL) Theory (Zimmerman, 2000) is relevant in that students who engage in self-regulated learning

may therefore alter acceptance of technologies such as ChatGPT as self-regulatory tools to support planning, information-seeking, feedback, explanation, self-assessment, and problem-solving, a view supported by (Ng et al., 2024). Hence, Barz et al. (2024) extended the technology acceptance model to include self-regulated learning and an affinity for technology.

This ties to the Technology Adoption Theory (Davis, 1989) and its iterations from TAM2 to UTAUT2, which have been widely applied to student technology adoption. The relevance is that the ODeL student is not simply learning with technology; technology is often part of the infrastructure through which learning occurs.

Hypothesis development

Behavioural intention (BI) can be defined as an individual's readiness to perform given behaviours (Camilleri, 2024). Research using the UTAUT2 generally focuses on all the model's core factors. For this reason, the impact of one or more factors on other factors is often reported. In developing the hypotheses for this research, only studies that reported the direct effect of a single factor on BI are reported. In addition, studies conducted in HEIs and those focused on AI adoption are preferred. The original hypotheses used by Strzelecki (2023) are re-employed but slightly adapted to highlight the use of ChatGPT in the current setting.

Performance Expectancy (PE) is defined as the "degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). Building on a long line of research, several authors have confirmed the predictive role of PE in BI in various settings, e.g., teachers' intentions to use mobile internet (Nikolopoulou et al., 2021), massive online courses (Amid and Din, 2021; Gupta and Maurya, 2022), and, of interest to the current research, at the university level (Arthur et al., 2025; Grassini et al., 2024; Faraon et al., 2025; Owan et al., 2025). A strong correlation with BI has also been confirmed in a meta-analysis of e-learning environments (Zheng et al., 2025) and in a study that found it has the greatest impact on BI across Norwegian universities (Grassini et al., 2024). The proposed hypothesis is:

H1: Performance expectancy has a direct and significant impact on behavioural intention to use ChatGPT

Effort Expectancy (EE) refers to "the degree of ease associated with the use of the system" (Nikolopoulou et al., 2021) and is often referred to as perceived ease of use. It is a significant predictor of BI, especially when combined with PE, and directly affects students' actual use of ChatGPT (Duong et al., 2023). EE is influenced by several factors, including the individual's prior experience with technology, their perceived technical ability, the technology's complexity, and the availability of resources and support for using it (Muriithi et al., 2016). The greater the perceived ease of use of a technology, the more likely an individual is to adopt and use it (Fagan et al., 2012). External social factors, such as peer recommendation and social media influence, play a moderating role (Bhaskar et al., 2024; Chen et al., 2025a), while contextual factors, including discipline, country, and demographic variables, influence its strength (Abdi et al., 2025; Linh, 2025; Owan et al., 2025). Actual use behaviour is often predicted by behavioural intention, with EE serving as a pathway to both intention and usage (Biswas et al., 2025; Ren et al., 2026; Sallam et al., 2024). In contrast, Alshammari et al. (2026) reported non-significant direct effects of EE on BI, while some prior studies have found a negative association between EE of Chatbots and chatbot usage intention (Ballesteros et al., 2025; Henkel et al., 2023). The proposed hypothesis is:

H2: Effort Expectancy has a direct and significant impact on behavioural intention to use ChatGPT

Social Influence (SI) refers to "the degree to which an individual perceives those important others believe he or she should use the new system" (Venkatesh et al., 2003, p.451).

In university settings, SI, including peer recommendations, word-of-mouth, and social norms, directly affects behavioural intention to use generative AI tools (Bahadur et al., 2024; Ballesteros et al., 2025; Uludağ et al., 2025). PE and EE have been shown to complement SI (Kai et al., 2026), while cultural dimensions, personal innovativeness and gender can moderate its effect (Goto and Ramnarain, 2026; Koteczki and Balassa, 2025). However, students may prioritise individual attitudes over social pressures (Ursavaş et al., 2025). SI is also consistently associated with BI across multiple countries and disciplines (Alotaibi and Alayed, 2025; Kılıç and Çelik, 2025; Li et al., 2018). However, several studies have reported weak or non-significant effects for social influence, pointing to a need to contextualise its role in technology adoption models (Ursavaş et al., 2025). The hypothesis forwarded is:

H3: Social influence has a direct and significant impact on behavioural intention to use ChatGPT

Facilitating Conditions (FC) refers to "the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003). Studying FCs in less-explored settings will advance the understanding and implementation of technology in education (She et al., 2025; Nurlaela et al., 2025). Several recent studies found that FCs have a significant positive effect on both BI and UB, e.g., (Alenazi and Alhalal, 2025; Chen et al., 2025b; She et al., 2025; Tran et al., 2025). (Romero-Rodríguez et al., 2023). FC has also been shown to be a critical determinant of both BI and UB in educational technology adoption, particularly when students perceive adequate support and infrastructure for technology use (Alenazi and Alhalal, 2025; Chen et al., 2025a; She et al., 2025; Tran et al., 2025;). On the other hand, studies of ChatGPT have reported that when resources are lacking in certain contexts, the effect is less pronounced or even negative (Owan et al., 2025; Sobaih et al., 2024). In some contexts, however, the effect is less pronounced or even negative when resources are lacking (Owan et al., 2025; Sobaih et al., 2024). Two hypotheses are constructed:

H4: Facilitating conditions have a direct and significant impact on behavioural intention to use ChatGPT

H5: Facilitating conditions have a direct and significant impact on use behaviour to use ChatGPT

Hedonic motivation (HM) is defined as "the fun or pleasure derived from using technology" (Venkatesh et al., 2012). While HM is frequently found to positively influence BI to use ChatGPT in higher education, often alongside utilitarian motivation, its relative impact, however, varies across disciplines and demographic groups (Abdi et al., 2025; Faraon et al., 2025; Foroughi et al., 2024; Kang et al., 2024). There are also complex interactions among motivational factors, such as attitudes and trust, and institutional factors (Rahman et al., 2023). Comparative studies show HM is a stronger predictor of BI in some contexts (e.g., STEM disciplines in Nordic countries) while utilitarian and social motivations take precedence elsewhere (e.g., USA, non-STEM) (Faraon et al., 2025; Qomariyah and Heriyanni, 2026). Here, the hypothesis is:

H6: Hedonic motivation has a direct and significant impact on behavioural intention to use ChatGPT

Habit (HT) has been defined as "the extent to which people tend to perform behaviours automatically because of learning" (Venkatesh et al., 2012). HT has been identified as a significant predictor of behavioural intention to use of educational technologies, which includes e-learning platforms, generative AI, and ChatGPT, thereby surpassing other UTAUT2 constructs (Bahadur et al., 2024; Romero-Rodríguez et al., 2023; Sergeeva et al., 2025; Singh et al., 2025; Zheng et al., 2024). Focusing on ChatGPT, recent studies Faraon et al. (2025) and Singh et al. (2025) have all shown that habit predicts both intention and actual use, with habitual engagement leading to greater acceptance. Other empirical studies show that HT formation strategies—such as repeated exposure, institutional support, and integration into routine academic activities—enhance technology adoption and sustained use (Bahadur et al., 2024; Sergeeva et al., 2025; Singh et al., 2025; Zheng et al., 2025). Two hypotheses forwarded are:

H7: Habit has a direct and significant impact on behavioural intention to use ChatGPT

H8: Habit has a direct and significant impact on behaviour to use ChatGPT

Several studies (Al-Adwan and Al-Debei, 2024; Amid and Din, 2021; Wang et al., 2026) have employed PI as both an intention and a use predictor in artificial intelligence studies. We add:

H9: Personal innovativeness has a direct and significant impact on the behavioural intention to use ChatGPT

Recent studies that reported BI to predict actual adoption/use behaviour of technology include significantly Kanahala et al., (2025) and A'ini et al., (2024), with Rana and Rai (2025), Strzelecki (2025), Grassini et al., (2024), Polyportis and Pahos (2024) and (Kaya and Adıgüzel, 2025) focusing specifically on ChatGPT. The hypothesis is:

H10: Behavioural intention has a direct and significant impact on behaviour to use ChatGPT

Mediators

Beyond the core factors covered above, meta-analytic evidence confirms that age, gender, and experience are the primary moderators in UTAUT2 influencing BI (Zahra et al., 2019). Depending on context, gender, and age, experience often moderates the relationship between facilitating conditions, behavioural intention, and actual use. For example, while Alenazi and Alhalal (2025) and Cabero-Almenara et al. (2025) reported significant moderation by gender or age, Xu et al. (2024) found no moderating effect. Romero-Rodríguez et al. (2023) showed that greater experience was associated with acceptance. In settings where academic integrity is a serious concern, anxiety, perceived risk, and ethical concerns may also moderate or mediate the relationship between effort expectancy and behavioural intention (Ahmed et al., 2026; Verano-Tacoronte et al., 2025; Qu and Wang, 2025). Furthermore, individual differences such as discipline, gender, and student background have been shown to moderate the importance of hedonic motivation. For instance, STEM students often report stronger hedonic motivation and more habitual use, while non-STEM students tend to show greater ethical anxiety and stronger social influence (Qomariyah et al., 2026; Kinskofer and Tulis, 2025). Other contextual variables, such as cultural orientation and income, also shape the influence of habit (Zheng et al., 2025; Kibria et al., 2026).

Method and measurement scale

In line with the Strzelecki (2023) approach, seven UTAUT2 predictors, focusing on behavioural intention to use and technology use behaviour, are employed. As with his study, "Price Value" is not used—the argument that ChatGPT, at least to some extent, is free to use. Predictors of interest are then "Performance Expectancy", "Effort Expectancy", "Social Influence", "Facilitating Conditions", "Hedonic Motivation", and "Habit". As motivated by Strzelecki (2023) and described by Agarwal and Prasad (1998), "Personal Innovativeness" is added as an additional predictor. It refers to the effects of antecedents (an individual's willingness and capacity to adapt to information technology) and consequences of individual perceptions, which involve a proactive, at times risk-taking, approach to innovation, openness to change, and eagerness to learn new things. This study employed a variance-based Structural Equation Model (PLS-SEM), which comprises reflective measurement models and a structural model with antecedents of Behavioural Intention (BI) and Use Behaviour (UB), as well as partial mediation through Personal Innovativeness (PI) as an additional predictor.

Table 1 presents the measurement-scale questions. Consistent with the standard protocol, operationalised by Muriithi et al. (2016) and recent applications of UTAUT2 to ChatGPT (Grassini et al., 2024; Strzelecki, 2023), UB was operationalised as a single-item measure using a seven-option frequency scale

TABLE 1 Measurement scale, construct reliability and validity.

CONSTRUCTS	ITEM	QUESTIONS	OUTER LOADING	α	CR (rho_a)	CR (rho_c)	AVE
PERFORMANCE EXPECTANCY	PE1	1. I believe that ChatGPT is helpful in my studies	0.410	0.630	0.731	0.782	0.490
	PE2	2. Using ChatGPT increases my chances of achieving important things in my studies	0.610				
	PE3	3. Using ChatGPT helps me get tasks and projects done faster in my studies	0.799				
	PE4	4. Using ChatGPT increases my productivity in my studies	0.884				
EFFORT EXPECTANCY	EE1	5. Learning how to use ChatGPT is easy for me *	0.861	0.914	0.916	0.939	0.795
	EE2	6. My interaction with ChatGPT is clear and understandable	0.917				
	EE3	7. I find ChatGPT easy to use	0.923				
	EE4	8. It is easy for me to become skilled at using ChatGPT	0.865				
SOCIAL INFLUENCE	SI1	9. People who are important to me think I should use ChatGPT	0.898	0.916	0.922	0.947	0.856
	SI2	10. People who influence my behaviour believe that I should use ChatGPT	0.948				
	SI3	11. People whose opinions I value encourage me to use ChatGPT	0.929				
FACILITATING CONDITIONS	FC1	12. I have the resources necessary to use ChatGPT	0.862	0.881	0.891	0.918	0.738
	FC2	13. I know how to use ChatGPT	0.906				
	FC3	14. ChatGPT is compatible with the technologies I use	0.894				
	FC4	15. I can get help from others when I have difficulties using ChatGPT	0.765				
HEDONIC MOTIVATION	HM1	16. Using ChatGPT is fun	0.839	0.861	0.870	0.915	0.783
	HM2	17. Using ChatGPT is enjoyable	0.901				
	HM3	18. Using ChatGPT is very entertaining	0.912				
HABIT	HT1	19. The use of ChatGPT has become a habit for me	0.849	0.889	0.892	0.923	0.750
	HT2	20. I am addicted to using ChatGPT	0.855				
	HT3	21. I must use ChatGPT	0.894				
	HT4	22. Using ChatGPT has become natural for me	0.862				
BEHAVIOURAL INTENTION	BI1	23. I intend to continue using ChatGPT in my studies	0.900	0.905	0.908	0.941	0.841
	BI2	24. I will always try to use ChatGPT in my studies	0.931				
	BI3	25. I plan to continue to use ChatGPT frequently outside my studies	0.919				
PERSONAL IINNOVATIVENESS	PI1	26. I like experimenting with new information technologies	0.830	0.858	0.873	0.903	0.699
	PI2	27. If I hear about a new information technology, I will look for ways to experiment with it	0.869				
	PI3	28. Among my family/friends, I am usually the first to try out new information technologies	0.836				
	PI4	29. In general, I do not hesitate to try out new information technologies	0.807				
USE BEHAVIOUR	UB	30. Please choose your usage frequency for ChatGPT	1.000	N/A	N/A	N/A	N/A

ranging from “never” to ’several times a day. Besides an attempt to minimise survey fatigue and the concise nature of the construct, Rossiter (2002) argued that single-item measures are perfectly valid when the object being rated is concrete and singular (ChatGPT) and easily understood by the respondent (e.g., “how often do you use this”).

Also included are the moderation effects of four demographic variables, namely Age (under the age of 30 or 30 and older),

Gender (male or female), Year of study (1st to 3rd year and above), and Status (full-time or part-time students, where part-time students are either working full- or part-time). Predictor data collection made use of a 7-point Likert scale with options ranging from "strongly disagree" to "Strongly agree". Thirty items, as used by Strzelecki (2023) and presented in Table 1, were presented through an online questionnaire. Figure 1 offers the model employed.

Results

Based on a student population of approximately 380,000 in 2025, assuming a conservative 50% response distribution, a 5% margin of error, and a 95% confidence level, an ideal sample size would be 384. However, based on survey responses in the current setting, the actual sample size was increased to 10,000. After ethical clearance, the ICT department randomly selected student email addresses from the institutional database. All students needed to be registered for a formal qualification. An invitation with a 4-week deadline to complete the online questionnaire was sent towards the end of 2024. A reminder post was sent after the deadline expired. Due to a slow response rate, the questionnaire was made available until March 2025, when it became clear that no further meaningful increase in responses could be expected. Although the final response rate was low (294/2.9%), it is considered appropriate for valid statistical procedures. It is noted that previous research at the institution also had a low response rate, even when data collection was extended to six months.

Sixty-five per cent of students were female, 74% under the age of 30, 76% in at least the 3rd year of study, and 54% were working full- or part-time. One reason for using some of these splits is that ODeL studies do not necessarily align with normal distributions at residential institutions; e.g., here, age does not necessarily equate with year of study, i.e., a 35-year-old student can be a first-year student. Another reason is the use of dummy variables as categorical moderators in PLS-SEM to ensure accurate modelling. Ninety percent (90%) of the respondents were from the HD group, which means many are possibly exposed to the challenges identified earlier in this paper. In general terms, the demographic data reflect the average institutional profile in terms of gender (71% female), age (62% aged 25–39), part-time study (40%—although this can change dramatically from year to year) and ethnic group (84% HD).

Model estimation and assessment

PLS-SEM offers several inner-weighting schemes: traditionally, centroid, factor (or factorial), and path-weighting, with empirical tests showing only marginal differences in results. Given its broader applicability to different model types and its tendency to yield higher explanatory power (R^2) for endogenous constructs, the path-weighting scheme is recommended (see Hair et al., 2022; SmartPLS documentation). Since the indicators are manifestations of the latent trait, the constructs were treated and evaluated as reflective (Hair et al., 2022). The assessment of reflective measurement models in PLS-SEM requires evaluating internal consistency reliability, convergent validity, and discriminant validity.

Internal consistency, indicator reliability and convergent validity

Table 1 reflects the measurement scale (constructs, items and questions) and the model, the outer loadings, Cronbach Alpha (α), composite reliability (CR) and average variance extracted (AVE). These measurements reflect internal consistency, indicator reliability and convergent validity.

Factor loadings show the extent to which an observed item strongly reflects its latent construct, typically evidenced by a high outer loading. According to Hair et al. (2022), indicator loadings ≥ 0.708 explain more than 50% of their variance. All constructs except PE had α and CR scores > 0.708 and AVE scores > 0.50, indicating meaningful factor loadings, good construct composite reliability, and internal consistency. Indicator PE1, which demonstrated a low outer loading of 0.410, was removed from the analysis to improve construct validity. Following its removal, the outer loading of the remaining indicator, PE2, rose to 0.695. Because it still fell short of the preferred 0.700 threshold, PE2 (0.610) was then considered for potential removal. While a two-indicator construct is generally less desirable than a three-indicator model, the joint removal of PE1 and PE2 significantly enhanced the psychometric health of the construct. Specifically, Cronbach's Alpha improved sequentially from 0.630 to 0.695, and ultimately to 0.721 (exceeding the 0.70 threshold). Concurrently, convergent validity (AVE) advanced from an unacceptable 0.490 to 0.621, and finally to 0.782, well above the 0.50 benchmark. This provided statistical justification for the decision and is in line with Parameswaran et al. (2015), who also removed PE1 and PE2 and reported acceptable internal consistency.

Multi-collinearity construct indicators

To analyse discriminant validity, the heterotrait–monotrait ratio of correlations (HTMT) method was employed. Following al.'s (2015) recommendations, an HTMT threshold of 0.90 was adopted because some of the constructs in the model (PE, EE, SI, FC, and HM) are conceptually related yet theoretically distinct (Nordhoff et al., 2021). Using bootstrapping, HTMT inference results were also considered. Our initial assessment showed that most HTMT values were below the recommended threshold of 0.90, except for Facilitating Conditions (FC) and Effort Expectancy (EE), which had an HTMT value of 0.909, thereby raising concerns about discriminant validity. Examination of the FC indicators showed that FC4 had the lowest outer loading (0.776). Although this loading was acceptable, FC4 was removed after assessing its impact on the overall measurement model. Following the removal of FC4, the HTMT value between FC and EE decreased from 0.909 (Table 2) to 0.882, thereby falling below the 0.90 threshold. In addition, the AVE for FC increased from 0.738 to 0.810, while composite reliability increased from 0.918 to 0.927, with Cronbach's alpha remaining virtually unchanged (0.881 to

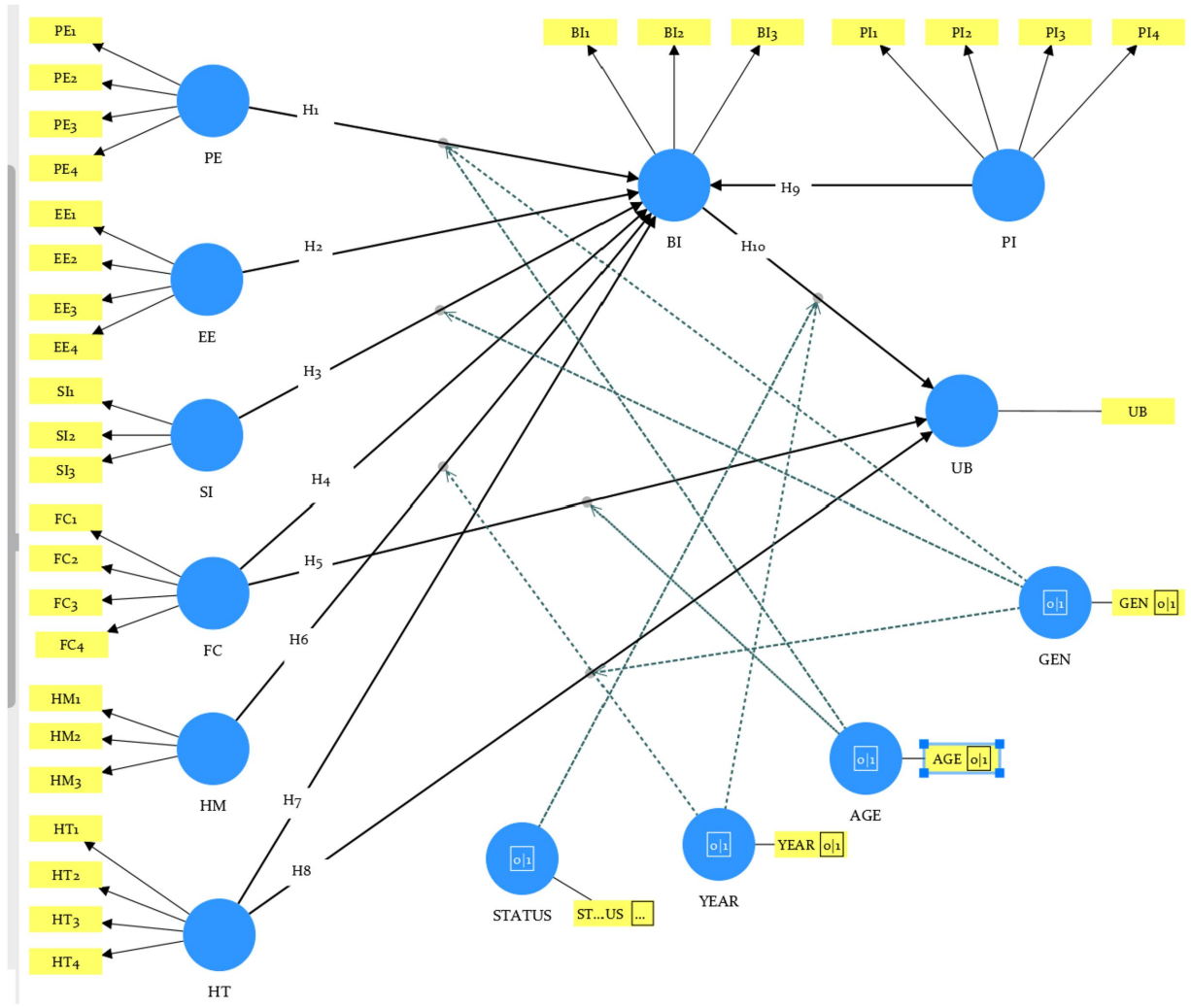

FIGURE 1
ChatGPT acceptance and use model employed.

TABLE 2 Heterotrait-monotrait ratio (HTMT) matrix of constructs.

CONSTRUCTS	BI	EE	FC	HM	HT	PE	PI	SI
EE	0.671							
FC	0.798	0.882						
GEN	0.061	0.036	0.034					
HM	0.727	0.866	0.846					
HT	0.784	0.699	0.694	0.790				
PE	0.768	0.869	0.738	0.770	0.725			
PI	0.737	0.762	0.758	0.786	0.631	0.692		
SI	0.662	0.821	0.729	0.845	0.790	0.778	0.714	
UB	0.423	0.592	0.510	0.641	0.600	0.557	0.578	0.578

0.882). The remaining FC indicators retained strong outer loadings ranging from 0.888 to 0.923. The removal of FC4 was therefore considered appropriate as it improved discriminant validity and convergent validity while retaining adequate theoretical coverage of the FC construct.

The square root of each construct's Average Variance Extracted (AVE) should also exceed its correlations with other constructs (Fornell and Larcker, 1981). Table 3 offers the off-diagonal values.

The table shows that the primary criterion is met for all constructs. Reflective indicator multicollinearity refers to

TABLE 3 Fornell-larcker criterion matrix of constructs.

Constructs	BI	EE	FC	HM	HT	PE	PI	SI	UB
BI	0.917								
EE	0.613	0.892							
FC	0.714	0.792	0.900						
HM	0.645	0.768	0.738	0.885					
HT	0.709	0.634	0.622	0.697	0.866				
PE	0.621	0.707	0.589	0.609	0.585	0.884			
PI	0.666	0.673	0.669	0.675	0.552	0.547	0.836		
SI	0.605	0.747	0.658	0.750	0.715	0.633	0.625	0.925	
UB	0.403	0.565	0.480	0.597	0.567	0.474	0.514	0.551	1.000

redundancy among items and is often screened indirectly via very high internal consistency rather than the Variance Inflation Factor (VIF). Since loadings and reliability already capture redundancy, a high redundancy may instead inflate α/CR (>.95). For transparency, VIF is nevertheless reported in Table 4. (Hair et al., 1995) argue that a VIF of 10 is acceptable, while Ringle et al. (2015) limit it to 5. In general, <3.3 (Kock, 2015), is desirable, while <5 is acceptable.

As reflected in the table, all constructs returned acceptable values, with 4 of the 10 below the desirable value of 3.3. If using Kock's full collinearity approach for common method bias, inner VIF < 3.3 suggests Common-Method-Bias (CMB) is also not a concern

TABLE 4 Variance inflation factor (VIF) for constructs.

Constructs	VIF
BI -> UB	3.825
EE -> BI	4.653
FC -> BI	3.507
FC -> UB	2.615
HM -> BI	3.859
HT -> BI	2.518
HT -> UB	2.857
PE -> BI	3.229
PI -> BI	2.322
SI -> BI	4.867

Coefficient of determination (R^2): base model

Table 5 presents the model's predictive accuracy. It represents the proportion of variance in BI and UB explained by all their connected predictor variables.

According to Hair et al. (2022), R^2 values of approximately 0.75, 0.50 and 0.25 may be interpreted as substantial, moderate and weak, respectively. The model explained 69.2% of the variance in BI ($R^2 = 0.692$), indicating substantial explanatory power. The model further explained 37.9% of the variance in UB ($R^2 = 0.379$), indicating moderate explanatory power.

The effect size (f^2) measures the relative impact of each construct. Although considered a weak measurement, it is nevertheless reported. The construct is considered to have a small effect if the f^2 value is between 0.02 and 0.14, medium if it is between 0.15 and 0.34 and large if it is greater than 0.35. FC -> BI, HT -> BI and HT -> UB returned medium effects, with the rest of the paths showing large effects. Finally, standardised Root Mean Square Residual (SRMR) values < 0.08 (conservative) or < 0.10 are typically considered acceptable for evaluating model fit (Henseler et al., 2015; SmartPLS Documentation). A value of 0.06 indicated a good model fit. Q^2 values of 0.647 and 0.302 indicated moderate and weak, but positive, predictive relevance for BI and UB, respectively. Although not considered a good measure, the effect sizes of the independent constructs ranged from negligible to large.

TABLE 5 Coefficient of determination (R^2).

Endogenous variable	R-square	R-square adjusted	Interpretation
BI	0.692	0.676	Substantial
UB	0.379	0.355	Moderate

Hypothesis testing

A hypothesis is accepted when the t-value is ≥ 1.96 and the p-value is < 0.05. Table 6 summarises the results.

The results indicated several significant direct effects ($p < 0.05$). Hypotheses accepted are:

H1: PE had a positive and statistically significant effect on BI ($\beta = 0.226$, t = 3.769, $p = 0.000$, 95% CI [0.118, 0.356]),

H2: EE had a negative but statistically significant effect on BI ($\beta = -0.258$, t = 3.089, $p = 0.002$, 95% CI [−0.428, −0.102]):

H4 and **H5**: FC had a positive and statistically significant effect on both BI and UB ($\beta = 0.429$, t = 6.532, $p = 0.000$, 95% CI [0.300, 0.559]), and ($\beta = 0.254$, t = 3.047, $p = 0.002$, 95% CI [0.093, 0.421]:

H7 and **H8**: HT had a positive and statistically significant effect on both BI and UB ($\beta = 0.384$, t = 5.793, $p = 0.000$, 95%

TABLE 6 Hypothesis testing.

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*P* values	f2	Supported
H1	PE -> BI	0.226	0.224	0.060	3.769	0.000	0.051	Accepted
H2	EE -> BI	−0.258	−0.257	0.084	3.078	0.002	0.046	Accepted
H3	SI -> BI	−0.072	−0.067	0.084	0.859	0.390	0.003	Rejected
H4	FC -> BI	0.429	0.427	0.066	6.532	0.000	0.170	Accepted
H5	FC -> UB	0.254	0.258	0.083	3.047	0.002	0.040	Accepted
H6	HM -> BI	0.023	0.021	0.078	0.292	0.770	0.000	Rejected
H7	HT -> BI	0.384	0.384	0.066	5.793	0.000	0.190	Accepted
H8	HT -> UB	0.576	0.578	0.073	7.880	0.000	0.187	Accepted
H9	PI -> BI	0.267	0.268	0.051	5.258	0.000	0.100	Accepted
H10	BI -> UB	−0.184	−0.188	0.093	1.972	0.049	0.014	Accepted

CI [0.254, 0.513]) and ($\beta = 0.0.576$, t = 7.880, $p = 0.00$, 95% CI [0.429, 0.716].

H9: PI had a positive and statistically significant effect on BI ($\beta = 0.267$, t = 5.258, $p = 0.000$, 95% CI [0.171, 0.368]) and

H10: BI had a negative but statistically significant effect on UB ($\beta = -0.0.184$, t = 1.972, $p = 0.049$, 95% CI [−0.371, −0.007]).

In descending order by size effect, the f^2 results indicate a medium effect for HT -> BI ($f^2 = 0.190$), followed by HT -> UB ($f^2 = 0.187$) and FC -> BI ($f^2 = 0.0.170$). Small effects were reported for PI -> BI ($f^2 = 0.100$), PE -> BI ($f^2 = 0.051$), EE -> BI ($f^2 = 0.046$), FC -> UB ($f^2 = 0.040$) and BI -> UB ($f^2 = 0.0.014$).

The two hypotheses**, H3**: SI has a direct and significant impact on BI to use ChatGPT, and **H6**: HM has a direct and significant impact on BI to use ChatGPT, are rejected with $p > 0.05$.

Additional analysis was conducted to investigate the unexpected negative relationship between EE and BI. The latent-variable correlation between EE and BI was positive (r = 0.613), while the EE path coefficient decreased from $\beta = 0.614$ ($p < 0.001$) in the EE-only model to $\beta = 0.193$ ($p = 0.024$) after PE and SI were added, before reversing to $\beta = -0.177$ ($p = 0.026$) when FC was introduced. The coefficient remained negative in the subsequent models, reaching $\beta = -.225$ ($p = 0.005$) in the full model. Concurrently, the EE VIF increased from 1.000 to 4.334. This pattern indicates that the negative EE coefficient is a conditional effect associated with the shared variance among the predictors and is consistent with a suppression effect.

Moderating effects

The moderating relationships of age, gender, year of study, and status (full- or part-time study) were incorporated into the model. Table 7 below shows the results.

Only one moderating relationship (YEAR × HM -> BI) reached statistical significance ($\beta = -0.188$, $p = 0.047$), indicating that the moderator weakened the relationship between the corresponding predictor and outcome variable. Two additional moderation effects approached significance ($\beta = 0.175$, $p = 0.077$; $\beta = -0.181$, $p = 0.094$), but they did not meet the t < 1.96 and/or the conventional 5% significance level.

Discussion and conclusions

Drawing on evidence from Africa's largest distance education institution, this research aimed to extend UTAUT2 to student use of ChatGPT in an under-researched ODeL context. The current research model, based on UTAUT2 (with Personal Innovativeness replacing Price Value in the framework), examined the determinants of Behavioural Intention (BI) and Use Behaviour (UB).

Whereas the interplay between predictors is usually reported in general UTAUT and UTAUT2 research, these are typically linked to different technology tools. With no systematic review of the interplay among UTAUT2 predictors reported in online ChatGPT studies, we will use a summary of the major rankings of significant predictors, along with moderators (if included), as extracted from 11 recent (2024–2026) studies. Nine of these studies were conducted outside Africa. The matrix is presented in Table 8. This approach will help compare the current findings to international patterns of ChatGPT adoption.

To provide a contextual overview, an attempt has been made to include one study from each country. Of particular interest are the predictor average rankings.

Our intention is not to provide a comprehensive up-to-date review, but to demonstrate how different predictors yielded different rankings, or no ranking, across countries. The rankings are based on SEM results using standardised path coefficients (β). Only statistically significant effects are included. Results for BI and UB, as well as for any reported moderators, are also shown. In the table, Ns denotes non-significant findings, while Nt indicates that the predictor was not assessed in the study. PE emerges as the most consistently important predictor of behavioural intention, followed by HT. HM and FC show moderate importance, while PI has promising but limited empirical support. EE and SI appear comparatively weaker and less consistent predictors of behavioural intention. BI (11) and FC (6) were reported as the most dominant drivers of UB.

TABLE 7 Moderating effects.

Moderator Paths	Original sample (O)	T statistics (|O/STDEV|)	*P* values	f2	Significant
AGE × FC -> UB	0.106	0.895	0.371	0.003	No
AGE × PE -> BI	0.081	1.130	0.259	0.004	No
GEN × HT -> UB	−0.181	1.677	0.094	0.011	No (marginal)
GEN × PE -> BI	−0.067	0.607	0.544	0.002	No
GEN × SI -> BI	0.049	0.443	0.658	0.001	No
STATUS × BI -> UB	−0.034	0.315	0.753	0.000	No
YEAR × BI -> UB	0.175	1.767	0.077	0.080	No (Marginal)
YEAR × HM -> BI	−0.188	1.982	0.047	0.017	Yes

While there are some consistencies, this comparison demonstrates that technology adoption is not necessarily uniform across global higher education contexts, even within Africa.

The positive and significant finding between Performance Expectancy and Behavioural Intention in the current study aligns with the original UTAUT2 model, but as the 4th-weakest among our 5 significant predictors, it contrasts with the research presented in Table 8, where it is the most consistently important predictor. Nonetheless, its significant role aligns with other non-ODeL research, such as Caner-Yıldırım (2025) and Camilleri (2024), who found Performance Expectancy to be a significant positive predictor of students' behavioural intention to use ChatGPT, as well as Chou et al. (2025), who reported that Performance Expectancy played a pivotal role in shaping Behavioural intention to use ChatGPT. We conclude that students who believed that ChatGPT would improve their performance or help them complete assignments more effectively were more likely to intend to use it, ostensibly to complete assignments faster, thereby increasing productivity. Given the percentage of working students in the current sample, this notion has merit.

Effort Expectancy not only ranked last among significant predictors of Behavioural Intention in the current study, but also returned a negative relationship. Its ranking is consistent with Table 8, where the relationship was weak, if not inconsistent. Whereas a positive relationship has been reported in research (Kaya and Adıgüzel, 2025; Parveen et al., 2026), it has also been found insignificant (e.g., Ahmed et al., 2026; Alshammari et al., 2026; Küçük and Çalışkan, 2026). The current finding specifically aligns with Henkel et al. (2023), who reported a negative association with chatbot usage intention. This suggests students who perceived the technology as easier to use were, paradoxically, less willing to adopt it. That is, the higher the effort expectancy, the less inclined they are to use the technology. That stated, the positive EE–BI correlation (r = 0.613) reported in the additional analysis indicates that students who perceive ChatGPT as easy to use generally report stronger intentions to use it. However, when other UTAUT2 predictors are controlled for, Effort Expectancy becomes negative ($\beta = -0.225$, $p = 0.005$). This, in turn, suggests that ease of use is not an independent driver of students' intention to use ChatGPT, and that the negative coefficient may reflect shared variance among closely related adoption factors rather than a genuine negative effect of ease of use. Another possible explanation is that as students become increasingly familiar with ChatGPT, ease of use may become less important in determining behavioural intention (Kaya and Adıgüzel, 2025), to the extent that recent higher-education studies have reported non-significant relationships between Effort Expectancy and Behavioural Intention (Salifu et al., 2024; Tian et al., 2024). In the ODeL context, students may therefore base their intention to use ChatGPT more on its perceived usefulness, effectiveness, and support for study demands and time management than on its simplicity.

Contrary to Table 8, in which 7 of the 11 studies found Social Influence to be a significant predictor of Behavioural Intention to use ChatGPT, our data did not support those results. At best, its weakest ranking in the table aligns with its non-significance in the current study, which shows that the opinions or encouragement of colleagues, friends, lecturers, or other important people did not influence participants' intention to use ChatGPT, possibly because participants are already familiar with it (Grassini et al., 2024).

As the 3rd-strongest predictor of Behavioural Intention to use ChatGPT, the finding that Facilitating Conditions is a significant positive predictor closely replicates its average ranking in Table 8 (4th). While its importance as a significant predictor has also been confirmed by Supianto et al. (2024) and Al-Zabadi and Jaradat (2025), both Shaengchart et al. (2023) and Bahadur et al. (2024) found it to be insignificant. Here, participants believed they had the necessary resources, knowledge, and technical know-how to use ChatGPT, making them more likely to intend to use it. This partly aligns with H3, in which support from others in using ChatGPT was not a factor.

Identified as a significant predictor of Use Behaviour in 7 studies (Table 8), Facilitating Conditions was also a significant predictor of Use Behaviour in the current study, but with $\beta = 0.254$ and $p = 0.0.40$, its effect was small. Note is taken of (Bahadur et al., 2024) who rejected it as a significant predictor of Behavioural Intention, but found it significant for Use Behaviour. Similarly, Parveen et al. (2026) reported it as a significant predictor of ChatGPT use. It is noted that Facilitating Conditions are often non-significant for Use Behaviour because other predictors sometimes mediate their effect (Nugraha et al., 2025). Although not explicitly tested, in the current study context, most students (90%) are from historically disadvantaged communities, which may affect access to infrastructure and technical resources.

TABLE 8 Predictor rankings across countries from recent ChatGPT research.

Authors/s	Predictors of BI							Significant Predictors of UB	Moderating variables of BI
	PE	EE	SI	FC	HM	HT	PI		
Strzelecki (2024) Poland	2	5	4	Ns	3	1	6	BI, FC	-
(Faraon et al., 2025) Case 1 Nordic countries	1	Ns	Ns	Ns	3	2	Ns	BI	-
(Faraon et al., 2025) Case 2 USA	1	Ns	3	Ns	Ns	2	Nt	BI	-
(Biyiri et al., 2025) Sri Lanka	2	Ns	1	3	Nt	Nt	Nt	BI, FC	-
(Arthur et al., 2025) Ghana	2	3	4	Nt	1	Ns	Nt	BI, FC	Age, gender
(Kaya & Adıgüzel, 2025) Eastern Europe	2	Ns	Ns	3	Ns	1	Nt	BI	-
(Grassini et al., 2024) Norway	1	Ns	Ns	Ns	Ns	2	Nt	BI	-
(Sabraz Nawaz et al., 2024) Sri Lanka	2	4	7	6	5	3	1	BI	-
(Owan et al., 2025) Nigeria	1	3	6	5	4	2	Nt	BI	-
(Chopra et al., 2025) India	1	4	3	2	Nt	Nt	Nt	BI, FC	Gender, study level
(Habibi et al., 2023) Indonesia	2	Ns	Ns	1	Nt	Nt	Nt	-	-

Ns, not significant ($p < .05$); Nt, not tested.

The finding that Hedonic motivation does not have a direct and significant impact on Behavioural intention to use ChatGPT is in stark contrast to its moderately strong ranking in Table 8, other research that did not focus on ChatGPT, and to a ChatGPT study by Abdi et al. (2025). Here, the results show that any enjoyment or fun associated with using ChatGPT did not significantly influence students' intention to use it.

In Table 8, Habit returned the 2nd-best ranking of Behavioural Intention across the studies. Here, it was the strongest and most significant predictor. This contrasts with Pham et al. (2025) and Arthur et al. (2025), who both found it to be insignificant in their studies of ChatGPT. This strong influence of Habit may be explained by the nature of the ODeL environment, in which learning is highly dependent on repeated, self-directed interaction with digital technologies. Frequent engagement with online learning platforms and ChatGPT can transform the use of technology from a deliberate decision into a routine component of students' study practices. Consequently, continued use of ChatGPT may be driven not only by its perceived usefulness or ease of use, but also by the extent to which its use has become embedded in students' established learning routines.

Likewise, Habit was also the strongest predictor of Use Behaviour. Other than Strzelecki (2023), a deeper literature search failed to identify any other study in which it was used as a predictor of actual use of ChatGPT. Our results then suggest that it is the most important factor influencing ODeL students' actual use of ChatGPT, who, when using it routinely, were substantially more likely to continue using it.

Employed as an extension of the current model, Personal Innovativeness was not only significant but also our 4th strongest predictor of Behavioural Intention to use ChatGPT. Used in only three of the studies in Table 8 and significant in two, the evidence is too limited to draw comparisons. The strongest other evidence found for Personal Innovativeness as a significant factor to use ChatGPT was Zogheib and Zogheib (2024). However, the authors noted that in their case, it did not relate to actual use. At best, it shows innovative students to have stronger intentions to adopt emerging technologies like ChatGPT. The clearest other research not supporting Personal Innovativeness to use ChatGPT is provided by Pasaribu et al. (2025).

The negative relationship between Behavioural Intention and Use Behaviour is unexpected from a UTAUT2 perspective, which conceptualises the former as a proximal determinant of actual technology use. The finding, therefore, does not support the theoretically expected positive relationship between intention and use. However, the relatively small coefficient ($\beta = -0.184$), marginal p-value ($p = 0.049$), and confidence interval that approaches zero suggest that the finding should be interpreted with caution. Furthermore, because Use Behaviour was measured using a single indicator, the result should not be over-interpreted as evidence of a substantive negative effect of behavioural intention on actual ChatGPT use. Rather, the finding indicates that, within the estimated structural model and

the specific study context, the observed relationship between intention and reported use differed from the relationship predicted by UTAUT2. Although not measured, if individuals expressed a stronger intention to use a technology but did not demonstrate greater subsequent use behaviour, the actual use of ChatGPT may depend on factors such as access, assignment types/difficulty, lecturer guidance and/or penalising and in the absence of use policies, uncertainty about acceptable use. The negative BI → UB relationship may also reflect the increasing role of habitual ChatGPT use, as research (e.g., Limayem et al. (2007) have shown that, with greater experience, technology use can become more routine and less dependent on consciously formed intentions. Such interpretation is consistent with the present finding that Habit was the strongest predictor of Use Behaviour.

Finally, the interaction of Year with Hedonic Motivation was the only significant moderator of Behavioural Intention. Here, as the study year increases, the positive influence of enjoyment (Hedonic Motivation) on students' intention to use ChatGPT becomes weaker, suggesting that students in the earlier years of study were more influenced by enjoyment when deciding whether to use ChatGPT. Given that students at an ODeL institution can be of any age (typically older), the term "study year" can take different meanings. This may partly explain why age was not a significant moderating variable.

In conclusion, the findings both support and build on earlier research into ChatGPT adoption in residential higher education. Although several of the UTAUT2 relationships held true, the predictors did not all carry the same weight. It can be concluded that for ODeL students, Facilitating Conditions emerged as the strongest predictor of Behavioural Intention to use ChatGPT, followed by Habit, Personal Innovativeness, and Performance Expectancy. Effort Expectancy was found to be negatively associated with Behavioural Intention. Social Influence and Hedonic Motivation were not significantly associated with Behavioural Intention. For Use Behaviour, Habit was the strongest predictor, followed by Facilitating Conditions, with Behavioural Intention negatively associated. Neither Social Influence nor Hedonic Motivation had a statistically significant relationship with Behavioural Intention. The addition of Personal Innovativeness, along with the moderating effect of year of study and Hedonic Motivation, indicates that ChatGPT adoption is shaped not only by the main UTAUT2 factors but also by students' individual traits and the ODeL learning context.

Taken together, this research has shown that, in this case, ODeL students' technology adoption both aligns with and differs from findings in other countries in some respects. However, if PI is removed from the current results, the predictor rankings are remarkably consistent with those of Owan et al. (2025) in Nigeria, and with the exception of Performance Expectation and Social Influence, broadly similar to Arthur et al. (2025) in Ghana. Taken together, the current study provides empirical evidence to inform strategies for globalising higher education. It suggests that institutions seeking to encourage the meaningful use of ChatGPT should focus on helping students develop regular habits, providing guidance and resources, and building their confidence in using the technology. They should also keep in mind that any intrinsic enjoyment derived from using ChatGPT seems to matter less as students progress through their studies.

Future research

Student diversity, synonymous with online distance learning, offers many new paths beyond the basic moderators employed in this study. For example, students may join from multiple countries, rural areas, and time zones, bringing diverse international perspectives to a multi-layered online learning environment. The negative relationships reported between Effort Expectancy and Behavioural Intention, and between Behavioural Intention and Use Behaviour, should be interpreted with caution and investigated further in future ODeL studies.

Investigating how deep intersectional demographics change ChatGPT adoption offers ample scope to propose and test new model boundaries in an ODeL context. A possible limitation of this study is the operationalisation of Use Behaviour as a single-item, self-reported frequency scale. While this aligns with the original UTAUT formulation (Venkatesh et al., 2003) and minimised participant burden, single-item scales cannot be tested for internal consistency reliability and capture frequency rather than the depth or duration of technology interaction. Future research should employ multi-item behavioural scales or objective, system-generated log data to validate the current findings.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Ethics statement

The research was approved by College of Science, Engineering and Technology School of Computing_ERCRef #: 3635. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

TMvdM: Writing – original draft, Writing – review & editing.

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