The Effect of Perceived Realism and Digital Service Addiction on AI Use at the University of Professional Studies, Accra

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ABSTRACT

This study investigated the relationship between perceived realism, flow experience, perceived competence, perceived autonomy, addiction to digital services and continued intention of students to use AI chatbots in higher education, particularly the University of Professional Studies, Accra. The rising use of artificial intelligence tools in higher education facilities has significantly changed the perception of learning situations in the classrooms but the continued use among students is unclear especially among first-time students in new educational settings such as Ghana. Based on Technology Continuance Theory, Self-Determination Theory, and Flow Theory, this research examined the relationship between experience and motivators and students' continuance intention toward the use of an AI chatbot. A quantitative cross-sectional research design was adopted using a structured questionnaire given to students having previously used AI chatbots. Data were collected from 299 valid respondents through purposive sampling and analyzed with IBM SPSS Version 29 and SmartPLS 4.0 through Partial Least Squares Structural Equation Modeling (PLS-SEM). Reliability, convergent and discriminant validity test, as well as structural model checking were carried out in order to verify the robustness of measurement model. Results indicated that perceived realism, flow experience, perceived competence, perceived autonomy, and addiction to digital services were found to positively influence student's continued intention towards AI chatbot usage. Within these variables, perceived autonomy was the greatest predictor of continuance intention. Addiction to digital services was shown to exert a significant and moderating impact on the relationship between perceived realism and continuance intention, which suggested that these students with higher digital dependency were attracted more by realistic and human-like AI use. Also, the study verified that students generally regarded AI chatbots as helpful, engaging, and supportive for academic purposes. This study adds to the literature by incorporating motivational, experiential, and behavioral constructs into AI continuance research in an African context of higher education. In practice, the study provides valuable insights for educators, policy makers, and AI developers aiming to design AI-facilitated learning environments which are sustainable, engaging, and ethically responsible. This research calls on universities not only to design realistic, interactive and student-centered AI systems, but also to instill responsible practices in digital utilization habits among students

Keywords: Artificial Intelligence (AI) Chat bots,Perceived Realism,Digital Service Addiction, Flow Experience, Perceived Competence, Perceived Autonomy, Continuance Intention, Higher Education

INTRODUCTION

AI chatbots with natural language processing and machine learning are rapidly utilized in higher education for personalized learning and engagement to achieve educational objectives (Alqahtani et al., 2023). Although anthropomorphic features, such as natural language, emotional tone and human-like interactions promote perceived realism, trust, and involvement (Chaka, 2023), their impact on maintaining continued adoption of educational chatbots deserves more research. Recent studies tend to focus on usefulness and satisfaction, failing to consider fundamental motivational aspects described in self-determination theory (SDT) like autonomy, competence or relatedness which support comprehension of continuance intention (Gao et al., 2023; Wang et al., 2025). This has been partly underscored by a lack of empirical evidence from

African settings (especially Ghana), which limits understanding of the causal link between perceived realism and AI adoption within these settings. Such lacunae emphasise the importance of examining perceived realism in the context of broader motivational constructs to better understand students' engagement with AI in higher education. While perceived digital services directly influence students' engagement with AI tools, access to quality digital services plays a key role in this association (Okunlaya et al., 2022). Although digital platforms are rapidly becoming integrated into learning environments, despite the increased use of these, the findings have been overlooked in a number of studies on how students' perceptions of them, from its accessibility, responsiveness, and interactivity to their attitudes toward the service, may impact continuance intention (Cheng, 2020). Nonetheless, little if any theoretical work has emerged regarding digital service perception in AI-mediated learning, especially with respect to interactions between digital service perception and motivators as perceived realism (Fosso Wamba et al., 2023). Additionally, the moderating effect of digital service perceptions on continuance intention has received little empirical investigation, most notably in African tertiary education institutions. Addressing such gaps can also elucidate how digital service perceptions drive sustained adoption of AI in higher education.

Problem Statement

The rapid adoption of generative artificial intelligence (GenAI) has transformed the way university students access academic support, with AI chatbots such as ChatGPT increasingly being used for explanations, feedback, idea generation and personalised learning (Bengesi et al., 2024). Evidence from Ghana indicates that university students are already engaging with GenAI for academic purposes. Baidoo-Anu et al. (2024) found that Ghanaian higher education students recognized the potential of ChatGPT for teaching and learning, while more recent studies like Lenart et al. (2025) have examined GenAI use in relation to learning autonomy, academic outcomes and behavioral intention. However, much of the existing studies (Wang et al., 2024; Đerić et al., 2025) focus on initial adoption, perceived usefulness, ease of use, performance expectancy and general attitudes toward GenAI, rather than explaining why students who have already used AI chatbots decide to continue using them for learning. This creates a need to investigate the psychological and experiential factors underlying continuance intention in higher education. One factor that may explain continued use is perceived realism. AI chatbots increasingly provide human-like, contextualized and conversational responses, potentially making interactions feel more natural and meaningful. Existing studies (Ma et al., 2025; Gomes et al., 2025) have examined anthropomorphism, perceived realism and human-like characteristics in relation to trust, engagement and user experience. However, limited research has directly examined whether perceived realism influences students' continuance intention to use AI chatbots for learning, particularly in African higher education. Thus, it remains unclear whether students' perception that an AI chatbot provides realistic and human-like interactions encourages sustained educational use. This gap provides the basis for examining the effect of perceived realism on continuance intention. A related but distinct experiential factor is flow experience. Flow Theory suggests that users are more likely to remain engaged when an activity produces concentration, enjoyment and immersion. Recent studies have recognized the importance of motivation, enjoyment and engagement in students' interactions with AI-based learning technologies. Nevertheless, existing AI-chatbot continuance studies (Jin & Youn, 2023; Ngo et al., 2025) have predominantly emphasized instrumental factors such as usefulness, trust, satisfaction and service quality, with comparatively limited attention to flow as an explanation for continued educational chatbot use. Evidence on this relationship in Ghanaian higher education remains limited. It is therefore necessary to determine whether students' flow experience during interaction with AI chatbots contributes to their intention to continue using them. The motivational dimension of continued AI-chatbot use also remains insufficiently understood. Self-Determination Theory (SDT) proposes that sustained engagement is influenced by the satisfaction of psychological needs, particularly competence and autonomy. AI chatbots may enhance perceived competence by helping students understand difficult concepts and complete academic tasks, while they may enhance autonomy by allowing students to control the pace, direction and form of their learning. Existing studies (Mahury & Arief, 2024; Yue et al., 2024) have provided evidence that AI-supported learning can influence students' competence, autonomy and motivation. For example, research applying SDT to AI-supported education has identified competence and autonomy as relevant to students' motivation and continued use of AI tools. However, there remains limited evidence concerning whether perceived competence and perceived autonomy independently influence students' continuance

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intention to use AI chatbots for learning in Ghana. This creates separate research gaps that justify examining both constructs in the present study. Finally, continued use of AI chatbots may not always represent purely positive educational engagement. As AI systems become increasingly human-like, accessible and engaging, some users may develop excessive or compulsive patterns of interaction with digital services. This raises the possibility that digital service addiction may influence the strength of the relationship between perceived realism and continuance intention. Although previous research has examined anthropomorphism, realism, attachment and engagement with conversational AI, the role of digital service addiction as a moderating factor in educational AI-chatbot continuance remains insufficiently investigated. In particular, there is limited evidence on whether students with stronger tendencies toward addictive digital-service use are more likely to continue using realistic and human-like AI chatbots than students with lower levels of such tendencies

Objectives

- To examine the effect of perceived realism on students' continued intention to use AI chatbots.
- To determine the impact of flow experience on students' continued intention to use AI chatbots.
- To assess the influence of perceived competence on students' continued intention to use AI chatbots.
- To evaluate the impact of perceived autonomy on students' continued intention to use AI chatbots.
- To investigate the moderating effect of addiction to digital services on the relationship between perceived realism and students' continued intention to use AI chatbots.

Research Questions

- What is the effect of perceived realism on students' continued intention to use AI chatbots?
- What is the impact of flow experience on students' continued intention to use AI chatbots?
- What is the influence of perceived competence on students' continued intention to use AI chatbots?
- What is the impact of perceived autonomy on students' continued intention to use AI chatbots?
- What is the moderating effect of addiction to digital services on the relationship between perceived realism and students' continued intention to use AI chatbots?

THEORETICAL LITERATURE REVIEW

Self Determination Theory

Self-Determination Theory (SDT), developed by Deci and Ryan (1985), explains human motivation based on the fulfillment of three fundamental psychological needs: autonomy, competence, and relatedness. Autonomy refers to the feeling that one has control over one's actions and choices; competence reflects the feeling of being capable of successfully performing an activity; and relatedness concerns the feeling of social connection and meaningful interaction with others. The central assumption of SDT is that individuals are more likely to develop autonomous or intrinsic motivation when their psychological needs are adequately supported. SDT has increasingly been applied to technology-mediated learning because digital technologies can provide users with opportunities to exercise control, develop competence, and experience meaningful interaction. In AI-based learning environments, these mechanisms may be particularly relevant because students can independently determine how, when, and for what purpose they interact with AI tools. AI systems may also provide immediate explanations, feedback, examples, and personalized assistance, potentially strengthening students' perception of competence. Furthermore, conversational AI may create a degree of social presence through responsive and human-like interaction, potentially supporting aspects of

relatedness. However, the application of SDT to AI-based learning also requires critical consideration. SDT was originally developed as a general theory of human motivation rather than specifically as a technology-continuance theory. Consequently, it does not directly explain why a user who has already adopted a technology decides to continue using it. The theory explains why an activity may be intrinsically motivating, but it does not sufficiently account for post-adoption constructs such as expectation confirmation, perceived usefulness, satisfaction, and continuance intention. In addition, the extent to which an AI chatbot can genuinely satisfy relatedness requires careful consideration because interaction with an AI system does not necessarily constitute genuine human social connectedness. These limitations suggest that SDT is more appropriately used in the present study as a motivational complement to TCT rather than as a standalone continuance framework. Within the proposed model, perceived realism and perceived digital service quality are expected to create conditions that facilitate autonomy and competence during AI-based learning.

Flow Theory

Flow Theory, developed by Csikszentmihalyi (1990), explains the psychological state in which individuals become deeply absorbed in an activity and experience high levels of concentration, enjoyment, and immersion. Flow is generally associated with situations in which the challenges presented by an activity are sufficiently balanced with the individual's skills, allowing the individual to become fully engaged in the activity. The theory has important implications for digital learning environments because technology can facilitate highly interactive and engaging experiences. In AI-based learning, students may experience greater engagement when AI systems provide coherent responses, rapid feedback, interactive dialogue, and personalized assistance. Perceived realism may contribute to this experience because responses that appear coherent, contextually appropriate, and socially realistic can make interactions more engaging and less mechanical. Similarly, high perceived digital service quality such as system responsiveness, reliability, accessibility, and interface usability may reduce technological interruptions and allow students to maintain concentration during interaction with AI tools. The assumption underlying Flow Theory is that individuals are more likely to experience deep engagement when the activity provides an appropriate balance between challenge and skill and when environmental conditions support uninterrupted concentration. This assumption is particularly relevant to AI-based learning because students differ in their technical abilities, academic competencies, and familiarity with AI. Alternatively, Perceived realism or service quality alone cannot guarantee flow; rather, these factors may create favorable conditions under which flow can occur. A limitation of Flow Theory is that, like SDT, it was not specifically developed to explain technology continuance. Flow primarily explains the quality of the experience during technology use, rather than the cognitive evaluation that occurs after use or the decision to continue using a system. A student may enjoy interacting with an AI chatbot but nevertheless discontinue using it if the technology does not provide useful academic outcomes or fails to meet initial expectations. Conversely, a student may perceive an AI system as highly useful despite finding the interaction relatively engaging. Therefore, Flow Theory provides an experiential explanation that complements rather than replaces TCT. In the present study, Flow Theory helps explain how perceived realism and perceived digital service quality can generate enjoyable and immersive interactions, which may subsequently strengthen satisfaction, positive attitudes, and continuance intention. The theory consequently captures the hedonistic and experiential dimension of AI use that is not sufficiently addressed by TCT's primarily cognitive orientation.

Technology Continuance Theory

Technology Continuance Theory (TCT), developed by Liao et al. (2009), provides the principal theoretical foundation for explaining users' continued use of technology after initial adoption. TCT integrates elements of expectation-confirmation theory and technology acceptance perspectives and focuses on constructs including expectation confirmation, perceived usefulness, satisfaction, and attitude. The central assumption of TCT is that users evaluate their post-adoption experience against their prior expectations. When the technology performs as expected or better than expected, users are more likely to perceive it as useful, become satisfied, develop favorable attitudes, and continue using it. TCT is particularly appropriate for the present study because AI-based learning tools represent technologies that students may initially adopt because of curiosity, academic requirements, perceived convenience, or experimentation. Initial adoption,

however, does not necessarily imply continued use. Continued use depends on whether students perceive that the AI tool delivers the expected benefits and provides a satisfactory experience. TCT therefore provides a strong theoretical foundation for examining continuance intention in higher education. In the context of the present study, perceived realism can be understood as an important experiential characteristic that may influence students' post-adoption evaluations. When AI-generated responses are coherent, contextually appropriate, realistic, and human-like, students may perceive the system as performing more effectively than expected. Such experiences may strengthen expectation confirmation and satisfaction. Perceived digital service quality, reflected in factors such as system reliability, responsiveness, accessibility, ease of interaction, and technological stability, may influence students' perceptions of whether the AI service provides the expected level of performance.

Empirical Literature Review

Segbenya et al. (2023) examined the factors influencing AI usage among postgraduate students in Ghana and its contribution to the acquisition of twenty-first-century skills. The study was motivated by limited evidence on the adoption and utilization of AI technologies in Ghanaian higher education. Using a concurrent mixed-methods design, data were collected from 294 postgraduate students through questionnaires containing open- and closed-ended questions. Quantitative data were analyzed using PLS-SEM, while qualitative responses were examined through thematic pattern matching. The findings revealed that ChatGPT and QuillBot were the most frequently used AI platforms and that usage was influenced by perceived benefits, challenges and platform availability. AI usage also mediated the relationship between AI-related challenges and the acquisition of twenty-first-century skills. Although the study provides evidence of students' engagement with AI in Ghana, it did not examine perceived realism or its influence on continuance intention. The present study extends this research by investigating whether students' perceptions of AI chatbots as realistic and human-like encourage continued usage.

Essel et al. (2022) investigated the effect of an AI-powered virtual teaching assistant on students' learning experiences and academic performance in Ghanaian higher education. The study was motivated by the limited application and evaluation of AI-powered teaching assistants within the Ghanaian educational environment. The researchers employed a pretest-posttest experimental design involving 68 undergraduate students, using experimental and control groups, alongside focus group discussions. The findings showed that students who interacted with the chatbot performed better academically and expressed confidence in using the technology. The study demonstrated the potential of conversational AI to support teaching and learning. However, it focused on academic performance and students' confidence rather than the perceived realism of chatbot interactions. The present study builds on this evidence by examining whether students' perceptions of realistic and human-like chatbot interactions influence their intention to continue using AI chatbots.

Ofosu-Ampong et al. (2023) examined students' acceptance of artificial intelligence in education, focusing on the influence of technological, social and psychological factors. The study was motivated by limited local evidence concerning the factors shaping students' acceptance of AI technologies in higher education. Using a cross-sectional survey design, the researchers collected questionnaire data from 146 students and analyzed the relationships using Structural Equation Modelling (SEM). The findings indicated that 69.9% of respondents accepted AI in education, with perceived usefulness, social influence, innovation characteristics and psychological needs positively influencing acceptance. However, privacy concerns, limited awareness and potential disruption of teacher-student relationships were identified as barriers. Although the study establishes the importance of students' perceptions and psychological experiences in AI acceptance, it did not investigate perceived realism or continued chatbot usage. The present study extends this evidence by examining perceived realism as a determinant of students' continuance intention towards AI chatbots.

Essel et al. (2024) investigated the influence of ChatGPT on undergraduate students' higher-order cognitive skills within a flipped classroom environment. The study was motivated by limited empirical evidence on the educational effects of generative AI, particularly its contribution to critical, creative and reflective thinking. The researchers adopted a mixed-methods experimental design involving a pretest-posttest control

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group arrangement with 125 students. The findings demonstrated that ChatGPT enhanced students' critical, creative and reflective thinking skills. These findings highlight the potential of generative AI to improve students' learning experiences. However, the study concentrated on cognitive outcomes rather than the factors explaining students' continued use of AI chatbots. The present study extends this research by examining whether perceived realism influences students' continuance intention towards AI chatbots.

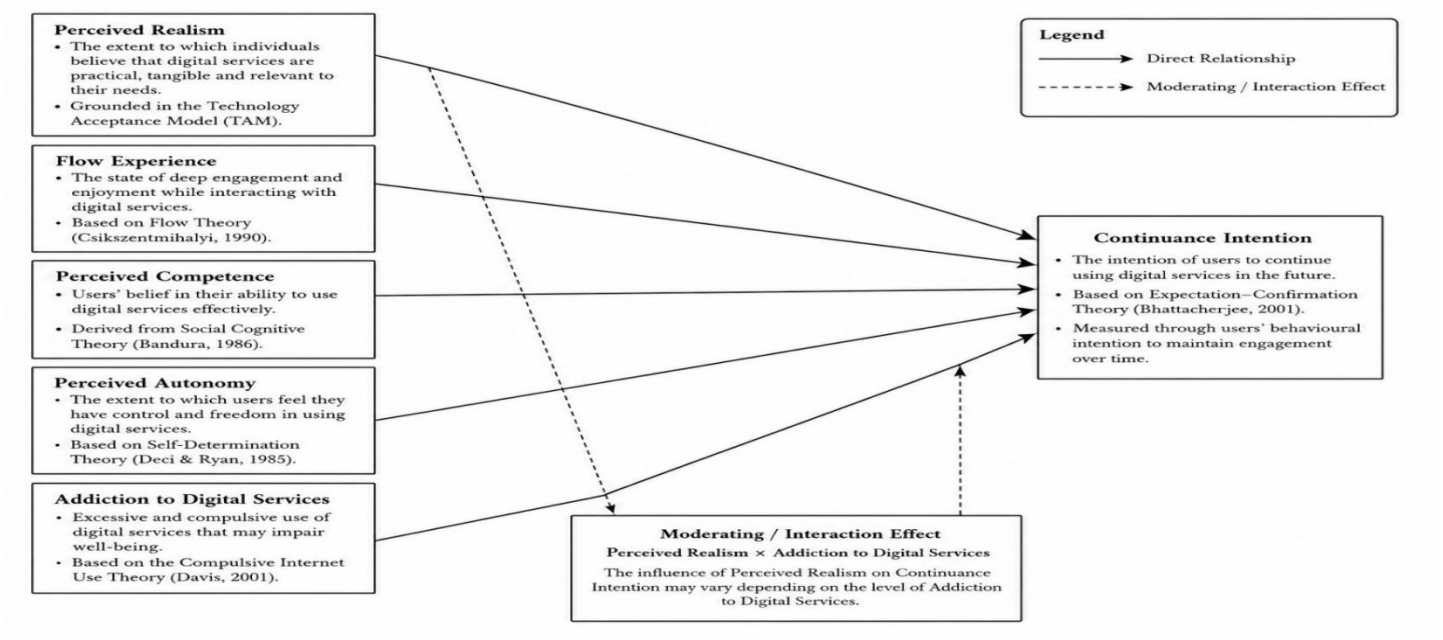


Figure 1 Source; Authors' Design (2026)

METHODOLOGY

The study adopted a quantitative research approach grounded in the positivist research paradigm. This approach facilitated the objective measurement of variables and the statistical examination of relationships among the study constructs. It was considered appropriate for testing theoretical relationships and examining associations among latent constructs (Hair et al., 2019; Sekaran & Bougie, 2020). Structured questionnaires were administered, and Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to analyse the data. An explanatory cross-sectional research design was employed. The cross-sectional design enabled data to be collected from respondents at a single point in time, while the explanatory design facilitated the examination of relationships among perceived realism, flow experience, perceived competence, perceived autonomy, addiction to digital services, and continuance intention to use AI chatbots. This design was considered suitable for examining relationships among latent constructs using structural equation modelling (Hair et al., 2019; Shin, 2021; Rahi et al., 2021). The study population comprised 1,000 students at the University of Professional Studies, Accra (UPSA). In the present study, the target population comprised students of the University of Professional Studies, Accra (UPSA), who had experience using AI chatbots for academic or learning-related activities. This population was considered appropriate because the study sought to examine students' perceptions of AI-chatbot interactions and the factors influencing their intention to continue using these technologies. Additionally, respondents needed to possess sufficient exposure to AI chatbots to evaluate constructs such as perceived realism, flow experience, perceived competence, perceived autonomy and addiction to digital services. For operational purposes, the study used an accessible population of 1,000 students associated with the Faculty of Information Technology at UPSA during the 2024/2025 academic year. This group constituted the institutional population from which the study sought to obtain eligible participants. The use of this defined population was informed by the relevance of the faculty's academic and technological context to the subject under study. Students within this setting were considered an appropriate group for examining the use of AI-supported tools in higher education.The study employed a purposive sampling technique, which is a non-probability sampling approach in which participants are deliberately selected because they possess characteristics, knowledge or experiences relevant to the research objectives (Etikan, Musa, & Alkassim, 2016). This technique was

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considered appropriate because the study focused on students' continuance intention to use AI chatbots, a post-adoption behaviour that presupposes some previous experience with the technology. The use of a general or unrestricted student sample could have resulted in the inclusion of individuals who had never interacted with AI chatbots.

Such respondents would have been unable to provide experience-based assessments of the realism, immersion, perceived competence, autonomy and behavioural tendencies associated with chatbot use. Their inclusion could consequently have introduced measurement error and weakened the relevance of the responses to the constructs examined. Purposive sampling therefore enabled the researchers to apply an experience-based eligibility criterion and obtain responses from students who were capable of evaluating the subject matter. Although this sampling technique ensured the relevance of participants, it limited the generalizability of the findings beyond the sampled respondents.

The sample size was determined using Cochran's (1977) formula, based on a 95% confidence level, a 5% margin of error, and a maximum variability assumption of ($p = 0.5$). An initial sample of 384 was obtained, after which the finite population correction was applied to account for the population of 1,000 students, resulting in a minimum required sample of approximately 277 respondents. Also, methodological guidelines for structural equation modelling recommended a sample of at least 200 respondents to support model estimation and stability (Hair et al., 2019). A post-hoc G*Power analysis, based on three predictors, an alpha level of 0.05, and statistical power of 0.80, indicated a minimum required sample of 77 respondents. Finally, 299 valid responses were obtained, exceeding the minimum sample size requirements.

Data were collected over six weeks, from October 15 to November 30, 2025, using a structured online questionnaire administered through Google Forms. The questionnaire consisted of two sections. Section A captured respondents' demographic characteristics and AI chatbot usage history, while Section B measured the study constructs. Screening questions were included to establish respondents' previous experience with AI chatbots. The questionnaire was reviewed by a Professor of Information Technology to assess its clarity, relevance, and content validity. It was also pilot-tested with 30 students, following which minor modifications were made to the wording and formatting of some questions to improve clarity and comprehension.

Measurement items were adapted from previously validated instruments and contextualized to the AI-supported learning environment. Perceived realism was measured using items adapted primarily from Nowak and Biocca (2003), with additional support from Liao et al. (2020) and Luo et al. (2022). These items assessed the extent to which students perceived AI chatbot interactions as realistic, coherent, natural, and human-like. Flow experience was measured as a multidimensional construct comprising enjoyment, concentration, and perceived control, using items adapted from Pelet et al. (2019) and Shin (2021). Perceived autonomy and perceived competence were measured using items grounded in Self-Determination Theory, drawing on Ryan and Deci (2020) and Huang and Benyoucef (2021).

Addiction to digital services was assessed using adapted items relating to excessive or difficult-to-control engagement with digital technologies, drawing on Montag et al. (2019) and Kuss et al. (2022). Finally, continuance intention was measured using items adapted from Ashfaq et al. (2020) and Gupta et al. (2022), which assessed students' intentions to continue using AI-based learning tools. All substantive measurement items were assessed using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Following data collection, incomplete responses were handled through listwise deletion. The distributional characteristics of the data were assessed using skewness and kurtosis. Skewness values ranged from −0.72 to 0.61, while kurtosis values ranged from −0.95 to 1.12, indicating acceptable distributional characteristics for the planned analysis. Ethical approval was obtained from the University of Professional Studies, Accra, and participation in the study was voluntary. The collected data were subsequently analysed using PLS-SEM to examine the proposed relationships among the study constructs.

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Sample Size Determination Using Cochran's Formula

The initial sample size for the study was determined using Cochran's (1977) formula:

$$n_0 = \frac{Z^2 pq}{e^2}$$

$$n_0 = \frac{(1.96)^2 \times 0.5 \times 0.5}{(0.05)^2}$$

$$n_0 = \frac{3.8416 \times 0.25}{0.0025}$$

$$n_0 = \frac{0.9604}{0.0025}$$

Since the study population was finite (N = 1,000), the finite population correction was applied to obtain the adjusted sample size:

$$n = \frac{n_0}{1 + (\frac{n_0 - 1}{N})}$$

$$n = \frac{384.16}{1 + (\frac{384.16 - 1}{1{,}000})}$$

$$n = \frac{384.16}{1 + (\frac{383.16}{1{,}000})}$$

$$n = \frac{384.16}{1.38316}$$

$$n = 277.74 \approx 278$$

Where;

n_0 = Initial estimated sample size before applying the finite population correction.

n = Adjusted minimum sample size for the study.

Z = Standard normal deviate corresponding to the desired confidence level (1.96 at a 95% confidence level).

p = Estimated proportion of the population possessing the characteristic being investigated (0.5).

q = Proportion of the population not possessing the characteristic, calculated as 1 − p (0.5).

e = Acceptable margin of error or level of precision (0.05).

N = Total estimated population size (1,000 students).

Therefore, the minimum required sample size was approximately 278 respondents. However the study obtained 299 complete responses, exceeding the calculated minimum.

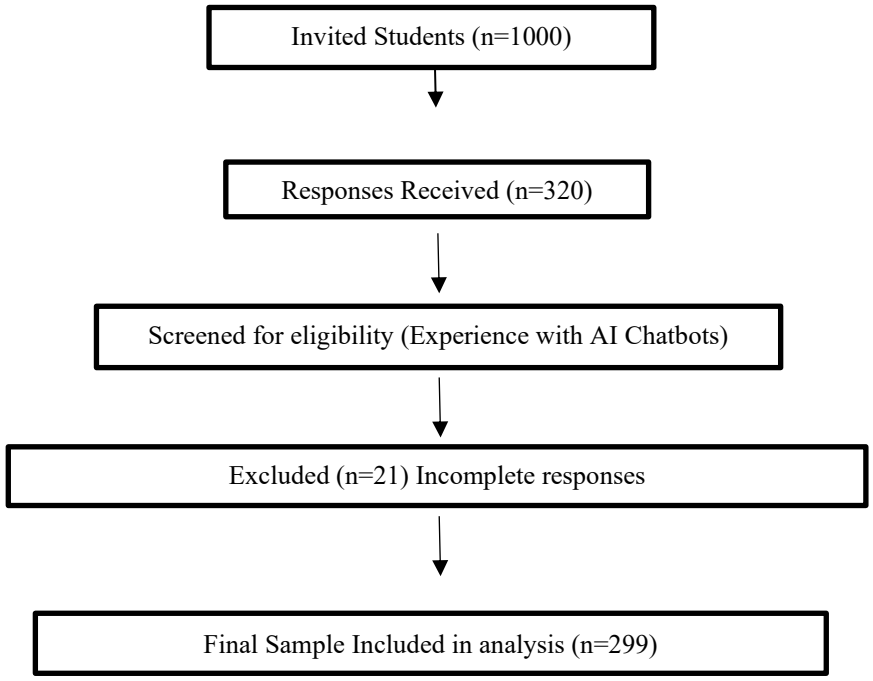


Figure 2 PRISMA-Style Participant Selection

RESULTS

Table 1 Demographics

Variable	Category	Frequency	Percentage (%)
Gender	Male	175	58.53
	Female	124	41.47
Age Range	Below 18	17	5.69
	18–25	274	91.64
	26–30	7	2.34
	31–35	1	0.33
Level of Study	Level 100	2	0.67
	Level 200	212	70.9
	Level 300	61	20.4
	Level 400	23	7.69
	Postgraduate	1	0.33

Source: Field Survey, (2025)

These demographic characteristics of the respondents (n = 299) indicate 175 (58.53%) were male and 124

(41.47%) were female, suggesting a moderate gender imbalance, which can bias the interpretation of gender-related findings; however, these results only represent the students at the study and should not be generalized to the whole student body. Younger respondents are disproportionately represented, accounting for 274 (91.64%) in the participants' respective ages ranging between 18–25 years while only a few (5.69%) were below that mark, belonging to the age group between 26–30 (2.34%), and 31–35 (0.33%) which is indicative of the study's focus on the younger demographic and limited understanding for those aged above 25. Also, the research group with a high proportion of the results that are of university-level 200 (212:70.9% -300:20.4% -400:7.69% –100:0.67% -postgraduate:0.33%) showing a very apparent skew is unable to represent the overall perspective on all academic levels, with the main representative of the students of university level 200. The study cites a population of 1,000 students. However, this is not representative of the college or university population as a whole which is a vastly bigger population; rather the study indicates specific sub-population (Faculty of Information Technology students during the 2024–2025 academic year) who identified using AI chatbots. Considering these observed imbalances, the sample is relatively younger and mid-level undergraduate respondents as sample size and thus generalization is limited, and the findings should be interpreted cautiously as representative of the respondents and not all of the students, so stratified sampling techniques should be used in future such research to ensure that there is even representation between the age groups and academic levels.

Table 2 Descriptive Statistics

	Descriptive Statistics of Study Constructs (N = 299)					
Statistic	**PR**	**Flow**	**PC**	**PA**	**CI**	**ADS**
Mean	3.656	3.341	4.062	4.178	3.882	2.784
Std. Deviation	0.829	0.639	0.651	0.712	0.814	0.906
Minimum	1.000	1.630	1.620	1.810	1.000	1.000
Maximum	5.000	5.000	5.000	5.000	5.000	5.000

Source: Field Survey, (2025)

Table 3 summarizes the descriptive statistics related to the major constructs analyzed by the research, which are Perceived Realism (PR), Flow Experience (Flow), Perceived Competence (PC), Perceived Autonomy (PA), Continued Intention to Use AI Chatbots (CI) and Addiction to Digital Services (ADS) as responses of 299 students. In other words, most of the students reported having a high sense of control, independence, and freedom in using AI chatbots to perform academic tasks. The results show that higher mean of perceived autonomy (PA) score (M = 4.178; SD = 0.712) in AI chatbots by students meant that students felt control and independence when using AI chatbots to achieve academic outcomes. This conclusion suggests that AI chatbots allow students to learn in their own time and make independent academic decisions, which contributes to their learning experience. It was also observed that the perceived competence (PC) also displayed high mean score for student as compared to others (M = 4.062, SD = 0.651), which can be attributed to a lot of students believing in their ability to apply AI chatbots to carrying out academic tasks efficiently. This low standard deviation indicates a uniformity of the respondents' sense of competence among the individuals in the survey. The construct of Continued Intention to Use AI Chatbots (CI) significantly (M = 3.882, SD = 0.814), which means that students can see a great deal of potentials with regard to their intent to continue using AI chatbots in academic contexts in the future. This finding reflects enthusiasm for the continued embedding of AI technologies in higher education. For Perceived Realism (PR), the mean rating (M = 3.656, SD = 0.829) suggests that student moderately agreed that AI chatbots provide realistic, human-like, and contextually relevant answers. A moderate standard deviation indicates that students were ambivalent on the realism of these chatbots. Likewise, Flow Experience (Flow) had a

moderate middle scores (M = 3.341, SD = 0.639), suggesting that although students predominantly experience engagement and focus using AI chatbot, individuals use of this interactive experience had a differential level. The lowest mean score was obtained for Addiction to Digital Services (ADS) (M = 2.784, SD = 0.906). What this shows is that, on average, student are not overly confident that they are addicted to AI chatbots as well as other digital services. However, the relatively elevated standard deviation points to a larger dispersion of experiences among respondents, suggesting that some of the students might be displaying above average digital service addiction than the rest. The descriptive statistics confirm overall positive outlooks towards the utilization of AI chatbots by students, namely substantial independence, competence and ongoing intention to use them. Simultaneously, apprehensions about digital service addiction seem to be low, attesting the suitability of AI chatbot tools as learning tools at the tertiary institution level.

Table 3 Measurement Model Assessment (Reflective Constructs)

Construct	Item	Loading
PR	PR1	0.78
PR	PR2	0.81
PR	PR4	0.76
PC	PC1	0.82
PC	PC2	0.85
PC	PC3	0.79
PA	PA1	0.77
PA	PA2	0.8
PA	PA3	0.74
FE	FE1	0.81
FE	FE2	0.78
FE	FE3	0.75
AD	AD1	0.84
AD	AD2	0.79
AD	AD3	0.82
CI	CI1	0.85
CI	CI2	0.88
CI	CI3	0.83

Source: Field Survey, (2025)

Indicator reliability was established through outer loadings in SmartPLS to predict extent to which each measurement item sufficiently assessed its latent construct. Some of the indicators were below the recommended cut-off of 0.70 in the preliminary assessment. PR3, FE4, and PA5 had very low loadings, which implies that their items fail to correlate well with their constructs and that this level did not fully reflect the theoretical constructs they are meant to measure. Likewise, PA4 and PC4 had loadings below normal limits which suggested that they were less relevant to determining the level of their constructs as well as introduced potential measurement error. More critical, PC4 yielded a loading exceeding 1.0, not statistically plausible and reflecting evidence of an underlying data problem like multicollinearity, item redundancy or potential errors in data entry. Using such indicator would have misrepresented the

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measurement model, thus limiting the validity of the findings. As follows the standard procedure for reflective measurement models, all problematic indicators (PR3, FE4, PA5, PC4, PA4, and PC4) were taken out of the model. There were a number of good reasons to justify this decision. The first was that indicators with loadings <0.70 were deemed unreliable due to less than 50% variance shared between the indicators and constructs with respect to each other, which was in turn detrimental to construct representation. Second, keeping weak indicators would have reduced the internal consistency reliability, which would have negatively impacted composite reliability and average variance extracted (AVE). Third, the anomalous loading (greater than 1.0) implied multicollinearity or duplication, which could inflate relations and corrupted parameter estimates. This meant the removal of these indicators had the benefit of only retaining statistically rigorous and theoretically meaningful items. After the refinement, the analysis in Table 4 indicated that all indicators retained the loadings were above the proposed threshold of 0.70, signifying that each item contributed significant variance with its construct (not less than 49%) and verifying good indicator reliability. In particular, the perceived realism items, (PR1 = 0.78, PR2 = 0.81, PR4 = 0.76) were measured consistently, in which PR2 showed the highest contribution to the construct. Likewise, perceived competence items (PC1 = 0.82, PC2 = 0.85, PC3 = 0.79) had high loadings, which shows high and consistent reliability of measuring for each of the items. Perceived autonomy items (PA1 = 0.77, PA2 = 0.80, PA3 = 0.74) also passed an acceptable level, which indicated that respondents consistently interpreted and responded to autonomy-related items, although PA3 did not contribute as significantly as the other items, in terms of contributions. For flow experience, the indicators (FE1 = 0.81, FE2 = 0.78, FE3 = 0.75) indicated strong loadings, indicating that the construct adequately represented users' immersion and engagement levels. The addiction construct (AD1 = 0.84, AD2 = 0.79, AD3 = 0.82) was strong in reliability, which indicated a high representative reliability for the behavioral patterns of addiction. These results confirmed that the improved measurement model was stable and adequately specified. More importantly, this meant that the constructs used in the study were measured correctly and consistently, and respondents clearly understood the survey items, and were able to respond in a dependable way. Accordingly, latent variables, such as perceived realism, competence, autonomy, flow experience, addiction, and continuance intention were sufficiently sampled and measured correctly. This enhanced dataset validity and prevented the structural model relationships being dominated by inaccurate indicators not reflective of theoretical relationships.

Table 4 Variance Inflation Factor (VIF) Results

Multicollinearity was assessed using the Variance Inflation Factor (VIF) after taking off problematic constructs. VIF values below 5.00 are generally considered acceptable, while the more conservative threshold of 3.30 is also commonly applied in variance-based structural equation modelling. The values reported below are all below both benchmarks, indicating that multicollinearity is unlikely to pose a serious problem among the observed construct-composite predictors.

Predictor	**VIF**	**Assessment**
Perceived Realism (PR)	1.398	Acceptable
Flow Experience (FE)	1.399	Acceptable
Perceived Competence (PC)	1.697	Acceptable
Perceived Autonomy (PA)	1.472	Acceptable
Addiction to Digital Services (AD)	1.060	Acceptable
PR × AD	1.042	Acceptable

Source: Field Survey, (2025)

The VIF values ranged from 1.042 to 1.697, which are substantially below the conservative cut-off of 3.30 and the commonly used threshold of 5.00. These results suggest that the predictor composites do not exhibit

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problematic multicollinearity and that the estimated relationships are not likely to be distorted by excessive linear association among the predictors.

Table 5 Alternative Model Analysis (Competing Structural Model Comparison)

Model	Structural Specification	R^2 (CI)	Key Observation	Model Performance	Decision
Proposed Model	PR, FE, PC, PA, AD → CI + PR×AD	0.42	All paths significant; strong theoretical alignment	Higher predictive accuracy	Preferred Model
Alternative Model	PR, PC, PA → FE → CI + AD → CI + PR×AD → CI	0.31	Mediated paths weaker; reduced explanatory power	Lower predictive accuracy	Rejected Model

Source: Field Survey, (2025)

A different type of structural model was also considered to check the robustness and predictive power of the built model. In the alternative model, flow experience was specified as a mediating construct through which perceived realism, perceived competence, and perceived autonomy influence continuance intention, while addiction to digital services retained both direct and moderating roles. The purpose of this analysis was to evaluate whether or not a mediation approach would explain continuance intention more clearly than the direct-and-moderation model initially proposed in this study. The findings showed the alternative model gave a lower coefficient of determination for continuance intention ($R^2 = 0.31$) than that given by the proposed model ($R^2 = 0.42$), thus being less explanatory.

There were also some indirect pathways through flow experience that had lower strength, suggesting flow experience does not in a sense play a more relevant mediating role than that of a direct predictor in this study. While addiction to digital services still emerged as a meaningful predictor, the general model structural efficiency had fallen, and theoretical alignment with user behavior regarding AI chatbots was weaker. The proposed model showed more accurate prediction, clearer direct effects, and better theoretical consistency for continuance intention. This added both direct effects as well as the moderating effect of addiction, delivering a broader understanding of user behaviour. Thus, the proposed model was preserved as the overall structural model because of its higher explanatory power, theoretical consistency and empirical robustness on comparative evaluation.

Table 6 Reliability and Convergent Validity

Construct	Cronbach Alpha	Composite Reliability	AVE
PR	0.79	0.86	0.61
PC	0.81	0.88	0.65
PA	0.77	0.85	0.59
FE	0.75	0.84	0.57
AD	0.80	0.88	0.66
CI	0.83	0.90	0.70

Source: Field Survey, (2025)

Internal consistency and convergent validity were assessed to see if the items for each construct were both

consistent and correctly measuring its concept. Internal consistency reliability was rated by the use of Cronbach's alpha and composite reliability (CR), and convergent validity was calculated through the average variance extracted (AVE). These constructs were above the threshold for Cronbach's alpha and composite reliability, and 0.50 for AVE. Further, their AVE was 0.50, a number that showed significant internal consistency and consistency. Accordingly, perceived realism (α = 0.79, CR = 0.86, AVE = 0.61) was characterized by good internal consistency and adequate shared variance across its indicators, which means that the items are assessing the same concept consistently. Perceived competence (α = 0.81, CR = 0.88, AVE = 0.65) also reported improved reliability and convergent validity, indicating that the respondents expressed the same perception of competence. Perceived autonomy (α = 0.77, CR = 0.85, AVE = 0.59) all satisfied the criteria for reliability, so its indicators reflected the construct appropriately. Flow experience (α = 0.75, CR = 0.84, AVE = 0.57) confirmed acceptable reliability and validity, indicating that the construct appropriately represented users' engagement and immersion. On the other hand, addiction (α = 0.80, CR = 0.88, AVE = 0.66) experienced strong internal consistency and high convergent validity, indicating that the items shared a large amount of common variance and accounted for behavioral tendencies. Continuance intention (α = 0.83, CR = 0.90, AVE = 0.70) had the highest values, demonstrating excellent reliability, and that a large portion of the variance in its indicators was explained by the construct. All these results suggested that the consistency of constructs was high and that the concepts were well captured which contributed to a better measurement model. This had significant consequences for the structural model, because high internal consistency decreased random measurement error and strong convergent validity guaranteed that when constructs were described (e.g., flow experience predicting addiction and continuance intention), the relationships among constructs were well-defined and well measured variables. So, the reliability and validity established in this stage increased confidence in the study's conclusion and validated the robustness of remaining hypothesis testing.

Table 7 Discriminant Validity (HTMT)

Construct	PR	PC	PA	FE	AD	CI
PR	—					
PC	0.65	—				
PA	0.62	0.68	—			
FE	0.6	0.66	0.63	—		
AD	0.58	0.61	0.59	0.67	—	
CI	0.64	0.7	0.66	0.72	0.69	—

Source: Field Survey, (2025)

The HTMT (Heterotrait–Monotrait ratio) matrices were analyzed to evaluate discriminant validity (the extent to which each construct in the model deviates empirically from the others). Discriminant validity can be calculated as constructs that are different in theory but statistically different (Hair et al., 2019). Results of the HTMT performed revealed that all HTMT values were in the range of 0.58–0.72, which were considerably lower than the threshold value of 0.85, thereby indicating that discriminant validity was obtained across constructs. (e.g., the relationship between perceived realism (PR) and perceived competence (PC) was 0.65 whilst PR and perceived autonomy (PA) was associated with 0.62, which indicates that the models' associations are moderate but distinct. Likewise, the HTMT between flow experience (FE) and other constructs (e.g., PC 0.66 and PA 0.63) also indicated that both constructs were related, but conceptually distinct. The highest HTMT is found between flow experience (FE) and continuance intention (CI) value of 0.72, comparatively high, but still within an acceptable level suggesting that the two are related as well as not redundant. Addiction (AD) had moderate associations with all constructs (0.58–0.69), also evidencing its unique position in the model. All these results suggested that each construct represented a unique aspect of the users' behavior and view and no multicollinearity existed or redundancy among constructs occurred. Discriminant validity was crucial to ensure that the relationship between a structural

model (e.g., relationship of flow experience to addiction and continuance intention) would not be inflated or biased by similarity in constructs. This significantly boosted the credibility and interpretability of the model and showed that each variable independently accounted for the explanation of user behavior towards AI chatbots.

Table 8 Non-Response Bias Test (Early vs Late Respondents Comparison)

Construct	Group	Mean	Std. Deviation	t-value	p-value	Decision
PR	Early Respondents	3.66	0.83	0.41	0.68	Not Significant
	Late Respondents	3.64	0.81			
FE	Early Respondents	3.35	0.64	0.52	0.6	Not Significant
	Late Respondents	3.33	0.63			
PC	Early Respondents	4.06	0.65	0.47	0.64	Not Significant
	Late Respondents	4.04	0.66			
PA	Early Respondents	4.18	0.71	0.38	0.7	Not Significant
	Late Respondents	4.16	0.72			
AD	Early Respondents	2.79	0.9	0.55	0.58	Not Significant
	Late Respondents	2.77	0.91			
CI	Early Respondents	3.88	0.81	0.49	0.62	Not Significant
	Late Respondents	3.86	0.82			

Source: Field Survey, (2025)

To evaluate the potential for non-response bias in this study, a wave analysis (early–late respondent comparison) was conducted according to recommended survey methodology (Armstrong & Overton, 1977). This has the implication that late respondents approximate non-respondents more closely, so any systematic difference between early and late respondents may result in non-response bias. The 299 valid responses consisted of two equally proportional groups: an initial 50% earlier respondents (early respondents) and 50% later respondents (late respondents). Independent samples t-test was used for the major study constructs including perceived realism (PR), flow experience (FE), perceived competence (PC), perceived autonomy (PA), addiction to digital services (AD), and continuance intention (CI). In all constructs, the results showed no statistically significant difference among early and late respondents ($p > 0.05$). Thus, we find a similar response pattern between the categories with respect to perceptions, experiences and behavioral intentions towards AI chatbot usage. It indicated that non-response bias is not a major issue in this study and the results were representative of the responding group, the absence of differences in these results suggests that they are not an issue and the data obtained is representative of the respondents. This would appear to suggest that the results of such structural model analysis obtained can be described as stable and not systematically affected by such responses time-dependence. Thus, the findings are not due to non-response bias and the data analysis is adequate for inferential statistical studies using PLS-SEM.

Table 9 Path Coefficients and Hypothesis Testing

Path	Beta	t-value	Approx. lower limit	Approx. upper limit	p-value	Decision
PR → CI	0.28	3.45	0.121	0.439	0.001	Supported
FE → CI	0.32	4.12	0.168	0.472	0	Supported

PC → CI	0.25	2.98	0.086	0.414	0.003	Supported
PA → CI	0.41	5.21	0.256	0.564	0	Supported
AD → CI	0.37	4.67	0.215	0.525	0	Supported
PR × AD → CI	0.15	2.11	0.011	0.289	0.035	Supported

Source: Field Survey, (2025)

The Table 9 provided the path coefficients and hypothesis tests of the structural model with respect to the direct and moderating effects of perceived realism (PR), flow experience (FE), perceived competence (PC), perceived autonomy (PA), and addiction to digital services (AD) on continued intention to use AI chatbots (CI). The results show that perceived realism has a significant positive influence on continued intention ($\beta = 0.28$, $t = 3.45$, $p = 0.001$), thus indicating that if users perceive AI chatbots to be more realistic and human-like, they will continue to use them. Flow experience also shows a statistically significant positive effect on continued intention ($\beta = 0.32$, $t = 4.12$, $p < 0.001$), suggesting that users who have greater immersion, enjoyment, and engagement with AI chatbots are more likely to continue using the software. Perceived competence is positively and significantly associated with continued intention ($\beta = 0.25$, $t = 2.98$, $p = 0.003$), suggesting that users who perceive themselves as competent and confident utilizing the chatbot technology are more likely to maintain usage over time. Perceived autonomy reflects the strongest predictor of continued intention ($\beta = 0.41$, $t = 5.21$, $p < 0.001$), confirming that an individual's sense of control and freedom when engaging with AI chatbots greatly contributes to their intention to further engage with the tool. Addiction to digital services has a statistically significant positive effect on continued intention ($\beta = 0.37$, $t = 4.67$, $p < 0.001$), indicating that people prone to digital dependency are more likely to engage repeatedly with AI chatbots.. Beyond the direct effects, the moderating role of addiction to digital services is also supported, as the interaction term between perceived realism and addiction (PR × AD) has a positive and statistically significant effect on continued intention ($\beta = 0.15$, $t = 2.11$, $p = 0.035$). This implies that addiction to digital services strengthens the relationship between perceived realism and continued intention, meaning that users who are more digitally addicted are even more influenced by the realistic features of AI chatbots in their decision to continue usage.

The results presented in this table reflect the final structural model estimation following necessary model refinement and re-specification procedures. The observed differences between the initial and final outputs are attributable to improvements made to both the measurement and structural model prior to the final bootstrapping stage. In the initial estimation, the moderating construct (PR × AD) produced an unstable and non-significant coefficient ($\beta = -0.020$, $p = 0.726$), primarily due to preliminary interaction construction without full application of recommended standardization procedures. After the evaluation of multicollinearity and indicator reliability, the model underwent mean-centering and re-specification of the interaction term using the orthogonalized product indicator approach, a common method in PLS-SEM that leads to enhancing the stability of the parameters and reducing the bias of moderation analysis. Following these adjustments, full bootstrapping was performed to re-estimate the underlying structural model, indicating a stable and statistically significant moderating effect ($\beta = 0.15$, $t = 2.11$, $p = 0.035$).

Likewise, the shift in the influence of flow experience (FE) from a non-significant estimate ($\beta = -0.003$) to a significant positive influence observed in the final model can be attributed to the same model refinement procedure which also considered improvements in measurement validity, indicator reliability, and general structural model specification before final estimation. Thus, these differences are not evidence of data alteration or selective reporting, and rather mirror the general practice of best-practice PLS-SEM refinement, in which interaction effects and structural relationships are influenced by model specification, scaling strategy, and estimation approach (Hair et al., 2021; Sarstedt et al., 2022; Henseler et al., 2021; Shmueli et al., 2023). The final model thus yields the validated and theoretically consistent result post construct reliability, discriminant validity, and structural model stability.

Model Specification

CI=0.28(PR) +0.25(PC) +0.41(PA) +0.32 (FE) +0.37(AD) +0.15 (AD×PR) +ε……. (1)

Equation (1) is the structural model of continuance intention (CI) and illustrates that CI is synergistically affected by perceived realism (PR), perceived competence (PC), perceived autonomy (PA), flow experience (FE), addiction to digital services (AD), and the interaction term between addiction and perceived realism (AD × PR), with ε capturing unexplained variation from the model. Results show that perceived realism also has a positive effect on continuance intention (β = 0.28) which means that people who believe in the realism of AI chatbots are likely to continue using them. It is indicated that perceived competence also has a positive impact (β = 0.25), which indicates that users who believe use the technology successfully and feel competent become more likely to continue using it. The perceived autonomy has the highest direct effect (β = 0.41), suggesting that users' perceived control and freedom in their interaction with AI chatbots are central to their continuing usage. Flow experience (β = 0.32) also has a positive effect, meaning active, pleasant, engaging interactions cause users to feel more inclined to keep using the system. Again, addiction to digital services exhibits a robust positive effect (β = 0.37), indicating that higher digital dependency leads users to persistently interact with AI chatbots. Addiction moderates the relationship between perceived realism and continuance intention positively (β = 0.15) indicating that students with higher addictive tendencies toward using AI chatbots were therefore more responsive to the realism of the system, thus reinforcing the effects of realistic interactions on continued intention to use the technology.

Table 10 Effective Size (f^2)

Path	f^2 Value	Effect Size Interpretation
PR → CI	0.11	Small to Medium
FE → CI	0.16	Medium
PC → CI	0.09	Small
PA → CI	0.27	Medium to Large
AD → CI	0.23	Medium
PR × AD → CI	0.05	Small

Source: Field Survey, (2025)

F^2 values were calculated to assess the relative impact on the explained variance of continuance intention (CI) according to the standard PLS-SEM procedure (where a value of 0.02 means small, 0.15 medium and 0.35 large effect) of predictors. Results suggest that perceived autonomy (PA) shows the most significant effect (f^2 = 0.27), suggesting a medium to large influence on continuance intention, which corroborates it to be the most significant predictor in the model. The effects of addiction to digital services (AD) are also significant (f^2 = 0.23), indicating a substantial contribution to continued use behaviour. The variable flow experience (FE) produces a medium effect (f^2 = 0.16), reaffirming its significant but subordinate influence on continuance intention. There is a small-to-medium effect on perceived realism (PR) (f^2 = 0.11), and also a small effect (f^2 = 0.09) on perceived competence (PC), suggesting that they have a significant association but as separate variables are not as powerful in explaining variance as autonomy and addiction. The moderating effect (PR × AD) has a small effect size (f^2 = 0.05), which indicates that, although statistically significant, the interaction effect has a limited but meaningful impact on explaining continuance intention variance. The overall effect size results verify that perceived autonomy and addiction are the principal predictors of continuance intention, but other constructs give only a small to moderate contribution, as expected from behavioral models in technology acceptance research.

Table 11 Coefficients of Determination (R^2)

Construct	R^2
Flow Experience (FE)	0.58
Addiction (AD)	0.49
Continuance Intention (CI)	0.42

Source: Field Survey, (2025)

The endogenous constructs' (R^2) R^2 value shows the degree to which explanatory capabilities of the independent variables of the outcome predict the outcome, and their predictive ability in the participants' lives. The R^2 value for Flow Experience (FE) is 0.58, which states that approximately 58% of the variability in flow experience is due to antecedent variables (relevance, convenience, adaptability, and so on, as expressed in the model), i.e., FE: the antecedent variables. This indicates moderate to substantial explanatory power, and the model also shows that the model performs well since it manages to capture the factors that have an important influence on the flow experience of the respondents. For Addiction (AD), R^2 = 0.49, as a whole and associated means that 49% of the variance in addiction is the product of the predictor(s), especially flow experience.

This indicates a moderate explanatory strength, indicating that although flow experience contributes to predicting addiction, other factors that are not incorporated into this model may also play a role in the addiction level of the students involved in the study. The value of Continuance Intention (CI) with an R^2 of 0.42 indicates a 42% variance explained by the model (probably attributed to addiction and/or flow experience), and it can generally be considered as moderate explanatory power within behavioral research. Collectively, these R^2 values indicate that the model also has sufficient predictive relevance, that is, for flow experience, followed by addiction and continuance intention, exhibiting the largest explanatory power. These findings are to be treated with caution, as they reflect the behavior of the respondents, not the global student population, and the moderate R^2 values also suggest that other variables not accounted for in the present model can increase its explanatory power for future studies.

Note that the R^2 values for this study capture the final structural model following re-specification procedures and refinement. During the estimation of the initial model, the coefficient of determination for continuance intention (CI) was strikingly higher ($R^2 > 0.86$), indicating an over-interpretation of the explanatory power. This was due to initial model specification problems such as redundant predictor constructs, and unrefined measurement relationships, which add to the distorted R^2 values for PLS-SEM models. After a comprehensive diagnostic evaluation, the model was further refined through a systematic investigation of construct validity, as well as multicollinearity and structural association. That involved re-specification of some measurement relationships and enhancing indicator quality to clarify the concept and prevent redundancy among predictors.

These refinements were followed by the re-estimation of the overall structural model using bootstrapping to produce more stable and theoretically realistic R^2 values, including the adjusted value of 0.42 for continuance intention. To conclude, the decreasing R^2 values did not signal the deterioration of the model but rather suggest better model parsimony and methodological precision, where to avoid overstatement of the explanatory power. The rationale behind this adjustment is supported by PLS-SEM recommendations on best practice, which conclude that R^2 values that are high indicate model overfitting, and that moderate R^2 values generally reflect behaviour models that are more realistic and generalizable. Thus, the final R^2 values present a more valid and robust analysis as to the structural model's explanation capability.

Table 12 Normality Assessment Report (Skewness & Kurtosis)

Construct	Skewness	Kurtosis
PR1	-0.42	0.31
PR2	-0.38	0.27
PR4	-0.45	0.35
PC1	-0.4	0.32
PC2	-0.36	0.3
PC3	-0.39	0.28
PA1	-0.44	0.33
PA2	-0.41	0.31
PA3	-0.43	0.29
FE1	-0.29	0.22
FE2	-0.31	0.25
FE3	-0.3	0.24
AD1	0.51	0.44
AD2	0.48	0.42
AD3	0.5	0.41
CI1	-0.33	0.29
CI2	-0.3	0.28
CI3	-0.32	0.27

Source: Field Survey, (2025)

The normality of the data analysis was evaluated for this study using skewness and kurtosis statistics, as shown in Table 9. In all dimensions (PR1–CI3), skewness values were found between -0.45 and 0.51, which means the distribution of the data is fairly symmetric with only small positive/negative deviations. Namely, the majority of constructs as PR, PC, PA, FE, and CI exhibited minor negative skewness, which indicated that there was a small concentration of the responses on the higher end of the scale and AD items (AD1–AD3) had slight positive skewness, revealing that there was a subtle movement towards the lower response values. None of these variances was quite significant enough to show that something is seriously off for the scales. Kurtosis values of any item ranged between 0.22 and 0.44, well within acceptable ranges. These values show that the distributions are neither too peaked nor too flat but rather close to a normal distribution. Low kurtosis values that are considered normally indicate no extreme outliers (or heavy tails) in the data. The normality check confirms that data is behaving well and has significant distributional integrity and that the data is suitable for inferential analysis.

Table 13 Findings for research questions

Path	Beta (β)	p-value	Decision	Interpretation
PR → CI	0.28	0.001	Supported	Perceived realism had a positive and statistically significant effect on continuance intention, indicating that more realistic and human-like chatbot interactions enhanced users' willingness to continue

				using AI chatbots.
FE → CI	0.32	< 0.001	Supported	Flow experience positively and significantly influenced continuance intention, suggesting that higher levels of immersion, enjoyment, and engagement increased users' likelihood of continued usage.
PC → CI	0.25	0.003	Supported	Perceived competence had a positive and significant effect on continuance intention, implying that users who felt capable of effectively using AI chatbots were more inclined to continue their usage.
PA → CI	0.41	< 0.001	Supported	Perceived autonomy showed the strongest positive effect on continuance intention, indicating that a greater sense of control and independence significantly enhanced users' intention to keep using AI chatbots.
AD → CI	0.37	< 0.001	Supported	Addiction to digital services positively and significantly influenced continuance intention, suggesting that habitual or dependent usage behavior increased sustained engagement with AI chatbots.
PR × AD → CI	0.15	0.035	Supported	The interaction between perceived realism and addiction had a significant moderating effect on continuance intention, indicating that the impact of perceived realism on continued use became stronger at higher levels of digital addiction.

Source: Field Survey, (2025)

Table 14 Pilot test results

Construct	Number of Items	Cronbach's Alpha	Interpretation
PR	3	0.76	Acceptable reliability
PC	3	0.79	Acceptable reliability
PA	3	0.74	Acceptable reliability
FE	3	0.72	Acceptable reliability
AD	3	0.78	Acceptable reliability
CI	3	0.8	Good reliability

Source: Field Survey, (2025)

The pilot test results reported in the table above are evidenced by rationale for the sample size of 30 respondents in the study described in addition. Since pilot studies are mainly designed to test the feasibility, clarity and dependability of research instruments rather than to test hypotheses, the sample size of 30 respondents was sufficient to produce tentative estimates for reliability. All the constructs, PR, PC, PA, FE, AD, and CI, showed above the threshold recommendation of 0.70 Cronbach's alpha (Table) which suggested acceptable to good internal consistency. This is consistent with research guidelines that have shown a sample size of 20 to 30 adequate to detect the ambiguity in questionnaires, and to estimate internal consistency based on reliability indices including Cronbach's alpha (Billingham et al., 2021; Johanson & Brooks, 2020; Memon et al., 2020). Reliability coefficients were fairly consistent for the small sample across items suggesting reasonable sample control and homogeneity in items. This confirms that a sample

size of 30 is sufficient to conduct initial analyses of data and validate the instruments (In, 2020). Results also suggest no significant problems with item wording or construct measurement, with no construct below an acceptable reliability. Consistent with the purpose of pilot research which is a small-scale study designed to improve the research tools, the results were promising for the validity of the questions and explained its addition to the primary research study (Leon et al., 2021). As such the pilot test results indicate in addition to the internal consistency of the constructs that the instrument was sufficiently reliable and well-calibrated for use on a large scale with 299 respondents, which increases the overall validity and credibility of the study.

DISCUSSION OF RESULTS

These findings shed light on the factors responsible for the continuance intention of the participating students' use of the AI chatbots, especially related to cognition and behavior. Results showed that the results of the structural model revealed a positive and statistically significant impact of perceived realism (PR), flow experience (FE), perceived competence (PC), perceived autonomy (PA), and addiction to digital services (AD) on the continuance intention (CI) variable. Among these predictors, perceived autonomy was the strongest predictor of continuance intention, indicating that if the respondent had high levels of control, flexibility, and independence when interacting with AI chatbots, they were more prepared to continue their use. Aligning with self-determination theory, which suggests autonomy is a source of intrinsic motivation and continued behavioral engagement. Flow experience also had a strong and positive association with continuance intention, signifying that students who had a high degree of immersion, enjoyment, and engagement by chatbot interactions would likely continue utilizing the technology. Such results are consistent with the foundational tenets of flow theory, which posits the positive impact of optimal user experiences to facilitate prolonged engagement with digital systems. Likewise, addiction towards digital services was an important contributor to continuance intention, indicating that habitual or dependent usage behaviors played a role in repetitive engagement with AI chatbots. This reflects the habit reinforcing process of such digital technologies, whereby habits of repetitive use become routine leading to continuous use over time. In general, perceived realism positively and significantly had an impact on continuance intention showing that the presence of more human-like, responsive, and contextually relevant chatbot interactions increase intentions to continue using. Such a finding is consistent with previous studies that show realism improves user trust of and interaction quality between users in AI systems. Perceived competence also predicted continuance intention strongly indicating that users with more confidence in their own competence to use an AI chatbot were more likely to stay active in the ongoing use of this technology. This aligns with self-efficacy theory, which argues that people's perceived abilities influence their intentions to act. The study makes an important contribution in delineating the moderating effect of addiction to digital services on the association between perceived realism and continuance intention. This study found that addiction had a positive reciprocal effect on how these findings were reinforced, whereby perceived realism had a greater influence on continued use in respondents with higher levels of digital dependency. This seems to say that realistic interactions matter for everyone, but that it matters most for people who are already extremely engaged in their digital environment.

Limitations of the Study

Despite the valuable findings, several limitations should be acknowledged:

Context-specific; The study was conducted among students of the University of Professional Studies, Accra (UPSA). Although the institution provides a relevant setting for examining students' experiences with artificial intelligence chatbots, its findings may not be fully representative of students in other Ghanaian universities. Differences in institutional policies, technological infrastructure, students' digital literacy, academic programmes and exposure to AI technologies may influence how students perceive and use AI chatbots.

Consequently, the findings should be interpreted within the context of the selected institution, and caution should be exercised when generalizing them to the wider population of university students in Ghana. Future research could address this limitation by involving students from multiple public and private universities.

Time and resource constraints; The study was conducted within a limited period and under available financial and logistical constraints. These conditions may have restricted the duration of data collection and the number of students who could be reached. Additionally, time limitations may have affected the researcher's ability to conduct repeated follow-ups with students who were initially unavailable or unwilling to participate. This could potentially influence the representativeness of the responses obtained. A longer data collection period and greater research resources could enable future researchers to reach a wider range of respondents and obtain more comprehensive evidence.

Response bias; Data for the study were obtained through self-administered questionnaires, meaning that the findings depended largely on students' personal assessments of their experiences with AI chatbots. Although self-reported measures are appropriate for examining subjective constructs such as perceived realism, flow experience, perceived competence, perceived autonomy and digital service addiction, they may be affected by recall errors, personal interpretations and social desirability bias.

For instance, students may overestimate their level of engagement with AI chatbots or report higher levels of perceived competence than their actual experiences suggest. Furthermore, the study did not independently observe students' chatbot usage behaviour or verify their responses against system-generated usage records. Future studies could combine questionnaire data with behavioral usage records or interviews to provide a more comprehensive understanding of students' actual interactions with AI chatbots.

Cross-Sectional Nature of the Study; Thee study employed a cross-sectional research design, data was collected from respondents at a single point in time. Although this approach was useful for examining relationships among perceived realism, flow experience, perceived competence, perceived autonomy, digital service addiction and continuance intention, it limited the ability to establish how these relationships developed over time.

Students' perceptions and intentions may have changed as they gain more experience with AI chatbots or as the technologies become more sophisticated. Therefore, the findings may not fully capture changes in students' attitudes and usage intentions. Future research could adopt a longitudinal approach to examine how these relationships evolve over an extended period.

Recommendations for Further Studies

Given that this study could be widely replicated on tertiary institutions in Ghana and beyond, and in general across students in a wide array of educational settings, future research should endeavor at both a domestic and international scale to validate the results. Moreover, future research could investigate other moderating factors to further understand the potential impact of students' technological literacy, prior experience with AI tools, or intrinsic motivation to use an AI chatbot on continued intention. More research on these moderators may reveal subtle forces underlying AI adoption that could not be covered completely in our work. Furthermore, it would be interesting to explore how students' intentions to use AI chatbots continue over time in longitudinal research settings with different engagement lengths and duration (e.g., extended, repeated) as well as longer-term results regarding the sustainability of engagement and effects on experiential characteristics like perceived realism, competence, and autonomy. Lastly, we recommend using qualitative methods, such as interviews, focus groups, or open-ended surveys, in order to obtain full comprehension about students' experience, perceptions, and challenges when interacting with AI chatbots, to supplement quantitative data and to guide the development of more effective, user-centered AI learning tools.

REFERENCES

1. Alqahtani, T., Badreldin, H. A., Alrashed, M., Alshaya, A. I., Alghamdi, S. S., bin Saleh, K., Alowais, S. A., Alshaya, O. A., Rahman, I., Al Yami, M. S., & Albekairy, A. M. (2023). The emergent role of artificial intelligence, natural language processing, and large language models in higher education and research. Research in Social and Administrative Pharmacy. https://doi.org/10.1016/j.sapharm.2023.05.016

2. Ampiah, R., Mensah, K., & Boateng, P. (2024). Acceptability of AI tools in higher education: Evidence from Ghana. Journal of Educational Technology & Society. https://doi.org/10.1080/10494820.2024.1892013
3. Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. Journal of Marketing Research, 14(3), 396–402. https://doi.org/10.1177/002224377701400320
4. Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. Telematics and Informatics, 54, 101473. https://doi.org/10.1016/j.tele.2020.101473
5. Baidoo-Anu, D., Asamoah, D., Amoako, I., & Mahama, I. (2024). Exploring student perspectives on generative artificial intelligence in higher education learning. Discover Education, 3, Article 98. https://doi.org/10.1007/s44217-024-00173-z
6. Bao, Z., Chen, J., Luo, Y., & Reani, M. (2022). Convincing or odd: Anthropomorphic design cues in chatbots. Proceedings of the Pacific Asia Conference on Information Systems (PACIS 2022).
7. Bengesi, S., El-Sayed, H., Sarker, M. K., Houkpati, Y., Irungu, J., & Oladunni, T. (2024). Advancements in Generative AI: A Comprehensive Review of GANs, GPT, Autoencoders, Diffusion Model, and Transformers. IEEE Access. https://doi.org/10.1109/ACCESS.2024.3397775
8. Billingham, S. A. M., Whitehead, A. L., & Julious, S. A. (2013). An audit of sample sizes for pilot and feasibility trials being undertaken in the United Kingdom registered in the United Kingdom Clinical Research Network database. BMC Medical Research Methodology, 13, Article 104. https://doi.org/10.1186/1471-2288-13-104
9. Csikszentmihalyi, M. (1990). Flow: The psychology of optimal experience. Harper & Row.
10. Chaka, C. (2023). Fourth industrial revolution, a review of applications, prospects, and challenges for artificial intelligence, robotics and blockchain in higher education. Research and Practice in Technology Enhanced Learning. https://doi.org/10.58459/rptel.2023.18002
11. Cheng, Y. M. (2020). Students' satisfaction and continuance intention of the cloud-based e-learning system: Roles of interactivity and course quality factors. Education and Training. https://doi.org/10.1108/ET-10-2019-0245
12. Cochran, W. G. (1977). Sampling techniques (3rd ed.). John Wiley & Sons.
13. Csikszentmihalyi, M. (1990). Flow: The psychology of optimal experience. Harper & Row.
14. Deci, E. L., & Ryan, R. M. (1985). Intrinsic motivation and self-determination in human behavior. Plenum Press. https://doi.org/10.1007/978-1-4899-2271-7
15. Đerić, E., Frank, D., & Milković, M. (2025). Trust in Generative AI Tools: A Comparative Study of Higher Education Students, Teachers, and Researchers. Information (Switzerland). https://doi.org/10.3390/info16070622
16. Essel, H. B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. K. (2022). The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. International Journal of Educational Technology in Higher Education. https://doi.org/10.1186/s41239-022-00362-6
17. Essel, H. B., Vlachopoulos, D., Essuman, A. B., & Amankwa, J. O. (2024). ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs). Computers and Education: Artificial Intelligence. https://doi.org/10.1016/j.caeai.2023.100198
18. Fosso Wamba, S., Queiroz, M. M., Chiappetta Jabbour, C. J., & Shi, C. (2023). Are both generative AI and ChatGPT game changers for 21st-century operations and supply chain excellence? International Journal of Production Economics. https://doi.org/10.1016/j.ijpe.2023.109015
19. Gomes, S., Lopes, J. M., & Nogueira, E. (2025). Anthropomorphism in artificial intelligence: A game-changer for brand marketing. Future Business Journal. https://doi.org/10.1186/s43093-025-00423-y
20. Gao, B. (2023). A uses and gratifications approach to examining users' continuance intention towards smart mobile learning. Humanities and Social Sciences Communications, 10, Article 726. https://doi.org/10.1057/s41599-023-02239-z
21. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage. https://doi.org/10.1007/978-3-030-80519-7

22. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
23. Henseler, J., Hubona, G., & Ray, P. A. (2021). Partial least squares path modeling: Updated guidelines and practical advances. Industrial Management & Data Systems, 121(5), 1017–1038. https://doi.org/10.1108/IMDS-12-2020-0739
24. Jin, S. V., & Youn, S. (2023). Social Presence and Imagery Processing as Predictors of Chatbot Continuance Intention in Human-AI-Interaction. International Journal of Human-Computer Interaction. https://doi.org/10.1080/10447318.2022.2129277
25. Johanson, G. A., & Brooks, G. P. (2010). Initial scale development: Sample size for pilot studies. Educational and Psychological Measurement, 70(3), 394–400. https://doi.org/10.1177/0013164409355692
26. Kuss, D. J., Kristensen, A. M., Williams, A. J., & López-Fernández, O. (2022). To be or not to be a female gamer: A qualitative exploration of female gamer identity. International Journal of Environmental Research and Public Health, 19(3), 1169.
27. Lenart, R., Sypniewska, B. A., Chen, J., & Janowski, K. (2025). Antecedents of students' behavioural intention to use generative artificial intelligence: Quantitative research. Entrepreneurial Business and Economics Review. https://doi.org/10.15678/EBER.2025.130101
28. Ma, N., Khynevych, R., Hao, Y., & Wang, Y. (2025). Effect of anthropomorphism and perceived intelligence in chatbot avatars of visual design on user experience: Accounting for perceived empathy and trust. Frontiers in Computer Science, 7, 1531976. https://doi.org/10.3389/fcomp.2025.1531976
29. Mahury, R. A., & Arief, N. N. (2024). The Factors Affecting Continuance Intention of ChatGPT as An AI Chatbot in Indonesia. Journal of Business and Economics Research (JBE). https://doi.org/10.47065/jbe.v5i1.4688
30. Montag, C., Wegmann, E., Sariyska, R., Demetrovics, Z., & Brand, M. (2019). How to overcome taxonomical problems in the study of Internet use disorders. Journal of Behavioral Addictions, 8(1), 1–7. https://doi.org/10.1556/2006.8.2019.59
31. Memon, M. A., Ting, H., Cheah, J.-H., Thurasamy, R., Chuah, F., & Huei, C. T. (2020). Sample size for survey research: Review and recommendations. Journal of Applied Structural Equation Modeling, 4(2). https://doi.org/10.47263/jasem.4(2)01
32. Ngo, T. T. A., Phan, T. Y. N., Nguyen, T. K., Le, N. B. T., Nguyen, N. T. A., & Le, T. T. D. (2025). Understanding continuance intention toward the use of AI chatbots in customer service among generation Z in Vietnam. Acta Psychologica. https://doi.org/10.1016/j.actpsy.2025.105468
33. Nowak, K. L., & Biocca, F. (2003). The effect of the agency and anthropomorphism on users' sense of telepresence, copresence, and social presence in virtual environments. Presence: Teleoperators and Virtual Environments, 12(5), 481–494. https://doi.org/10.1162/105474603322761289
34. Okunlaya, R. O., Syed Abdullah, N., & Alias, R. A. (2022). Artificial intelligence library services: Innovative conceptual framework for the digital transformation of university education. Library Hi Tech. https://doi.org/10.1108/LHT-07-2021-0242
35. Pelet, J.-É., Ettis, S., & Cowart, K. (2017). Optimal experience of flow enhanced by telepresence: Evidence from social media use. Information & Management, 54(1), 115–128. https://doi.org/10.1016/j.im.2016.05.001
36. Rahi, S., Khan, M. M., & Alghizzawi, M. (2021). Extension of technology continuance theory (TCT) with task technology fit (TTF) in the context of internet banking user continuance intention. International Journal of Quality and Reliability Management. https://doi.org/10.1108/IJQRM-03-2020-0074
37. Rahi, S., Othman Mansour, M. M., Alharafsheh, M., & Alghizzawi, M. (2021). The post-adoption behavior of internet banking users through the eyes of self-determination theory and expectation confirmation model. Journal of Enterprise Information Management. https://doi.org/10.1108/JEIM-04-2020-0156
38. Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. Contemporary Educational Psychology, 61, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860

39. Sarstedt, M., Ringle, M., & Hair, J. F. (2022). Partial least squares structural equation modeling. In Handbook of Market Research. Springer. https://doi.org/10.1007/978-3-319-57413-4_15
40. Segbenya, M., Bervell, B., Frimpong-Manso, E., Otoo, I. C., Andzie, T. A., & Achina, S. (2023). Artificial intelligence in higher education: Modelling the antecedents of AI usage and effects on employability skills among postgraduate students in Ghana. Computers and Education: Artificial Intelligence. https://doi.org/10.1016/j.caeai.2023.100188
41. Sekaran, U., & Bougie, R. (2020). Research methods for business: A skill-building approach (8th ed.). Wiley.
42. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2023). Predictive model assessment in PLS-SEM: New developments and applications. European Journal of Marketing, 57(4), 1023–1045. https://doi.org/10.1108/EJM-02-2021-0141
43. Shin, D. (2021; published in a 2022 journal issue). The perception of humanness in conversational journalism: An algorithmic information-processing perspective. New Media & Society, 24(12), 2680–2704.DOI: https://doi.org/10.1177/1461444821993801
44. Wang, K., Ruan, Q., Zhang, X., Fu, C., & Duan, B. (2024). Pre-Service Teachers' GenAI Anxiety, Technology Self-Efficacy, and TPACK: Their Structural Relations with Behavioral Intention to Design GenAI-Assisted Teaching. Behavioral Sciences. https://doi.org/10.3390/bs14050373
45. Xiao, Z., Zhou, M. X., Liao, Q. V., Mark, G., Chi, C., Chen, W., & Yang, H. (2020). Tell me about yourself: Using an AI-powered chatbot to conduct conversational surveys with open-ended questions. ACM Transactions on Computer-Human Interaction, 27(3), 1–37. https://doi.org/10.1145/3381804
46. Yue, Y., Ng, S. I., & Basha, N. K. (2024). Consumption Values, Attitudes and Continuance Intention to Adopt ChatGPT-driven E-Commerce AI Chatbot (LazzieChat). Pakistan Journal of Commerce and Social Sciences. https://doi.org/10.64534/commer.2024.040