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RESEARCH PAPER

A theoretical investigation of students' adoption of artificial intelligence chatbots using social cognitive theory and gratification theory

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Abstract

Prior studies widely acknowledge artificial intelligence as a facilitator of digital transformation in the educational sector. Yet, research on the determinants of AI chatbot adoption among students in low – and middle-income countries, particularly Ghana, is scarce. This study addresses this gap in the literature by investigating the motivational and behavioral antecedents that influence students' use of AI chatbots in Ghana. Using Chat GPT – a type of AI chatbot, this research adopts the Uses and Gratification and social cognitive theories. Based on survey data from 249 study participants, this study employed the partial least square structural equation modeling approach. The study's findings reveal that confidence, convenience, control, and enjoyment significantly affect students' satisfaction. Also, satisfaction affects the use of AI chatbots among students in Ghana. Furthermore, some findings of our study diverge from previous research by revealing that identity does not significantly affect students' satisfaction in the context of AI chatbot adoption.

Keywords: AI chatbot, students, Determinants, Low and middle-income countries, Social cognitive theory, Uses and gratification theory.

Introduction

A technological initiative that has arisen as an innovative and effective solution that offers students access to personalized learning resources and educational content (Chen *et al*., 2020) is artificial intelligence (AI). AI refers to "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein & Kaplan, 2019, p. 5). AI includes Meta's BlenderBot, Google's LaMDA, Open AI's Chat GPT, and Microsoft's Copilot (O'Leary, 2022). We focus on Chat GPT – a popular type of AI in low and middle-income countries that provides rapid information access, study assistance, writing support, and research guidance to students.

The explosive diffusion of AI chatbots, coupled with the characteristics of mobile devices such as mobility and flexibility, are expediting the increase in assisted learning and information access among students in low and middle-income countries, particularly Ghana. Thus, AI is touted as an innovative and effective enabler in deepening digital inclusion since it provides personalized learning and information resources to many students in Ghana (Ankamah *et al*., 2024).

Extant literature on AI reveals that researchers have focused on AI adoption in developed countries (e.g., Knox, 2020; Rauf *et al*., 2021) at the expense of low – and middle-income countries like Ghana. For example, Knox (2020) analyzed AI adoption in China's educational context with an emphasis on the implications of integrating AI in teaching and learning in China. Their study focused on the socio-economic and geopolitical implications of AI development as an integral part of China's educational context. Also, Rauf *et al*. (2021) examined students' perceptions of AI adoption in Germany and the Netherlands. The writers sought to understand the factors that influence AI perception and the implications for future employment opportunities. The authors argue for a need to explore the factors that drive the actual use of AI in educational contexts. Hence, it is essential

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to advance knowledge in this area by conducting more encompassing studies that account for the antecedents of actual use behavior concerning AI adoption among students in Ghana, a lacuna this research seeks to fill.

Moreover, prior research on AI adoption has drawn on technology acceptance theories that emphasize technological drivers of AI adoption (e.g., Wang *et al*., 2021; Ghimire & Edwards, 2024). Such research efforts leave under-explored other motivational and behavioral antecedents that facilitate AI use among students. The use of AI among students in Ghana is hinged on (1) the complex integration of mobile devices and AI chatbots (Wang *et al*., 2021), and (2) the complex interaction of students' educational needs and mobile technologies (Pillai *et al*., 2024). Yet, only a handful of studies have adopted motivational and behavioral theoretical perspectives to analyze the antecedents of the use of AI use among students in Ghana. Therefore, there is a need to adopt an integrated theoretical approach to investigate the antecedents of AI use in such contexts.

We complement existing literature on the antecedents of AI chatbot adoption among students in Ghana from an integrated theoretical perspective. Consequently, we combine the uses and gratification theory (UGT) and the social cognitive theory (SCT). The uses and gratification theory assesses motivational antecedents, while the social cognitive theory examines the cognitive dimensions in relation to AI adoption among students in Ghana. We address the following research questions: *(1) what are the antecedents that influence the use of AI among students in Ghana?*

Our research advances knowledge in the following areas. First, we unravel the antecedents to the use of AI among students in low and middle-income countries. Insights on actual use behavior have research and practical implications. Also, we complement existing literature on AI adoption in the educational sector in low – and middle-income countries by proffering insights from motivational and behavioral perspectives.

The research is organized as follows. The next section presents a discussion of AI adoption among students, the uses and gratification theory, and the social cognitive theory. The third section presents the hypotheses and research model. The fourth section presents the methodology. This is followed by results and analysis in the fifth section. The sixth section presents a discussion, theoretical contributions, as well as practical implications. Section seven concludes the study and discusses study limitations.

AI chatbot adoption among students

AI chatbots accessed *via* digital platforms are considered innovative ways to enhance learning among students in Ghana. Research on AI chatbots in the educational sector has emphasized areas such as the exploitation and use of AI for learning and language practice (Chen *et al*., 2020). Also, Chang *et al*. (2022) examined the use of mobile chatbots as a learning tool to improve nursing students' self-efficacy. Moreover, Fryer *et al*. (2019) investigated the use of a human chatbot as a tool to enhance language learning engagement. The study suggests that students who have task interests increase in learning via human-chatbot interactions. These studies shed light on the growing impact of AI in the educational sector across the globe. However, existing literature on AI adoption has explored the phenomenon from perspectives other than learning purposes among students, particularly in Ghana (Pillai *et al*., 2024). Therefore, there is a need for further theorization of this phenomenon to address the gap in the literature.

The Uses and Gratification Theory

The UGT was first developed by Lazarsfeld & Stanton (1944) to provide insights into why people use mass media and the gratification they derive from it. UGT contends that media use and selection are purposive (Blumler & Katz, 1974). Thus, users have needs and actively engage in addressing those needs by using a variety of media (Rubin, 2009). Gratification refers to the satisfaction obtained from the active use of media by media users (Stafford *et al*., 2004). Hence, we define gratification in this study as the satisfaction obtained from using AI chatbots.

Fundamentally, UGT is used as a theoretical underpinning to investigate the motivations of users that determine media consumption and how this influences satisfaction (Ku *et al*., 2013). Furthermore, UGT elucidates the motives behind media use, the determinants of these motives, as well as media use outcomes (Valentine, 2011). UGT has been applied across several disciplines to investigate mass media use (Kang & Atkin, 1999) and social media use (Chen & Chan, 2017). This is because UGT provides a more robust explanation of usage by accounting for the intrinsic and extrinsic motivations of users actively engaged in media use (Luo *et al*., 2011).

Educational institutions in developing countries tend to have varying levels of technology infrastructure and accessibility, immature social, political, and economic systems, unique cultural contexts, and limited resources. These disparities and challenges often reinforce instances of the digital divide (Friederici *et al*., 2017), which shapes the development of specific needs and aspirations that influence students' satisfaction with AI chatbots. Hence, UGT has significant implications for our study since we seek to investigate students' satisfaction with AI chatbots.

Although UGT has been widely adopted because of its explanatory capabilities in unearthing how people use digital tools to address specific needs (Hechanova & Ortega-Go, 2014) and for personal development (Liu *et al*., 2020), it is more inclined toward the satisfaction users seek out that leads to usage, at the expense of why users seek out specific gratifications or engage specific media behaviors

(Stafford *et al*., 2004). Focusing solely on the gratifications users seek out that lead to usage without an understanding of why users seek out specific gratifications does not give a holistic understanding of the determinants of students' AI chatbot use, considering the significant variance between "the gratification users seek out" and "why users seek out such gratifications." Hence, we adopt UGT as one of the theoretical lenses for the study and complement it with SCT.

Social Cognitive theory

Developed by Bandura (1997), SCT suggests that the behavior of individuals is a result of their cognition in the social environment they find themselves. Thus, SCT enhances our understanding of the behavioral characteristics of individuals. Also, Bandura (1997) suggests that two fundamental cognitive forces influence people's behavior. These are outcome expectations and self-efficacy. Self-efficacy refers to "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p. 3). Also, Bandura (1997) suggests that people perform certain behaviors when they are confident in their ability to perform such behaviors. On the contrary, people are bound not to perform certain behaviors once they have no confidence in their ability to perform such behaviors, particularly in a context where performing such behavior is voluntary. Hence, we do not consider self-efficacy in this study, following Chiu *et al*.'s (2006) work. Outcome expectations can be described as the expected consequence associated with one's behavior (Bandura, 1997). Outcome expectations in SCT are characterized by three main forms: physical effects (e.g., enjoyment and convenience), social effects (e.g., identity), and self-evaluation effects (e.g., personal control and confidence) (Bandura, 1997). Given that these outcomes influence satisfaction, we draw on SCT to understand how the physical effect, social effects, and self-evaluation effects influence students' satisfaction with AI chatbots.

Hypotheses development and research model

Researchers (e.g., Iyamu, 2013) suggest that combining theories to investigate a phenomenon provides a holistic understanding. We draw inspiration from this argument and combine UGT and SCT to investigate students' satisfaction with AI chatbots. Whereas UGT addresses motivational drivers, SCT focuses on behavioral antecedents. Hence, we propose a research model with the following variables: confidence, convenience, identity, control, enjoyment, satisfaction, and use. The research model is presented in Figure 1.

Hypotheses

Confidence

Confidence represents a consumer's belief that his or her attitude, knowledge, or ability is sufficient or correct regarding a product (or object/stimuli) (O'cass & Natarajan, 2003) Confidence refers to the assurance and users' impressions of service providers' competency, transparency of agents, and their capacity in assisting customers in resolving ambiguity and fears (Siau & Shen 2003). Also, Hunneman *et al*. (2015) demonstrate that the relationship between service attributes and customer satisfaction is stronger in periods where consumer confidence is low. The work of Al Qaisi and Alrosan (2020) suggests that confidence has a significant influence on customer satisfaction. In this study, confidence is defined as the degree to which students believe or are certain that they can use AI chatbots without difficulty. AI chatbot features such as user-friendly interfaces and instant feedback increase students' confidence in their ability to navigate such digital platforms without prior experience, thereby increasing their satisfaction. Thus, we posit that:

- *H1*

Confidence will significantly influence students' AI chatbot satisfaction

Convenience

Convenience is choosing the quickest or simplest path to achieve a goal (Gottschalk, 2018). People favor convenience when it saves time and effort, eliminating anguish and uncertainty (Gottschalk, 2018). The work of Kurniawan *et al*. (2019) indicates that convenience significantly affects customer satisfaction. In this study, we define convenience as the degree to which students can access digital content rapidly and conveniently, without hindrances, using AI chatbots. Regardless of location and time, AI chatbots provide accessible and relatively affordable learning resources to students. Such convenience will increase students' satisfaction. Thus, the study posits that:

- *H2*

Convenience will significantly influence students' AI chatbot satisfaction

Identity

Identity is defined as the qualities, beliefs, personality, looks, and/or expressions that make a person (Gutiérrez-Agüero *et al*., 2021), as well as their perception and affiliation with various social groups such as nationality, ethnicity, religion, gender, or profession (Shen *et al*., 2021). It reflects the complex interaction between one's sense of self and social context, shaping their roles, relationships, and sense of belonging within a larger societal framework (Bamberg, 2011). Chowdhury *et al*. (2014) suggest that identity improves satisfaction. In this study, we define identity as students' perceived self-privilege to use AI chatbots to access resources online. AI chatbots offer a sense of belonging to a global tech-savvy learning community. This sense of identity allows students to associate themselves with the digital

ecosystem and trending technologies. This boots students' self-esteem and motivates them to engage actively with AI chatbots, increasing their satisfaction. Therefore, we argue that:

- *H3*

Identity will significantly influence students' AI chatbot satisfaction

Personal control

Control is the ability to influence behavior, the outcome of oneself, or a situation to meet fluctuating environmental demands or internal goals (Zhu *et al*., 2016). Personal control is an individual's ability to regulate and manage their thoughts, emotions, actions, and behavior. Empirical studies have shown that personal control affects satisfaction (Zhu *et al*., 2016). In this study, we define personal control as students' ability to regulate their behavior in AI chatbot usage. AI chatbots provide several information and learning resources round-the-clock, mobile-friendly or web accessibility options, and flexible scheduling that suits students' preferences. This empowers students and gives them personal control, which will increase their satisfaction. Thus, we posit that:

- *H5*

Personal control will significantly influence students' AI chatbot satisfaction

Enjoyment

Enjoyment refers to perceived intrinsic motivation based on the pleasure or fun experienced using an electronic device (Puriwat & Tripopsakul, 2017). According to Hsu & Lin (2018), enjoyment is the extent to which a person believes that using technological services would provide pleasure and personal satisfaction. Empirical studies from different contexts (e.g., Bae *et al*., 2020) have shown that enjoyment significantly influences satisfaction. In this study, we define enjoyment as the pleasure and fun students derive from using AI chatbots. AI chatbots provide visually appealing interfaces, interactive content, and flexible as well as convenient access, making students' experiences more pleasurable. These pleasurable experiences will increase their satisfaction. Therefore, we hypothesize that:

- *H5*

Enjoyment will significantly influence students' AI chatbot satisfaction

Satisfaction

Satisfaction is the measure of the performance of a product or service against the actual performance of the product or service (Rosli & Nayan, 2020). Empirical studies (e.g., Tam *et al*., 2020) found satisfaction to significantly influence the usage behavior of consumers in mobile banking and e-commerce contexts. In this study, we define satisfaction as the perceived performance of AI chatbots that meet students' expectations in terms of usability, accessibility, content quality, and engagement. Students are more likely to develop a positive attitude towards the actual use of AI chatbots when they perceive that the system satisfies their needs. Thus, we posit that:

- *H6*

Satisfaction will significantly influence students' actual use of AI chatbot

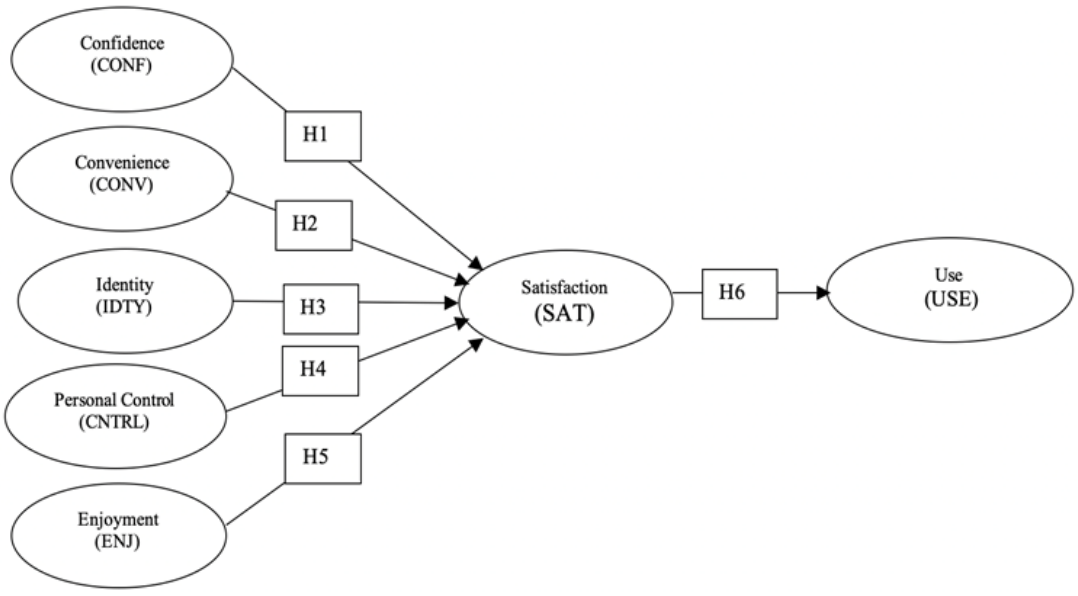

Figure 1: Research model

Methodology

Setting

We conducted this research at the University of Professional Studies Accra (UPSA), a thriving public institution in Ghana known for its unflinching commitment to innovation and academic excellence. Specifically, we focused on students' use of AI chatbots, particularly Open AI's Chat GPT. This research context was chosen due to its well-established technological infrastructure and focus on leveraging innovative technologies to enhance educational service delivery. In light of these significant characteristics, we examined students' adoption of Chat GPT at UPSA as the focal point for the empirical research.

Research design

The study employed a cross-sectional survey method and quantitative techniques to analyze the data. The researchers designed a 5-point Likert scale online questionnaire using Google Forms, which ranged from strongly disagree to strongly agree. The items used for the study were adapted from the literature. The online questionnaire was appraised by 3 lecturers and 3 students for content validity. Based on the suggestions and comments raised by the validation team, the researchers streamlined the wording, arrangement of items, and formatting of the online questionnaire. The online questionnaire was divided into 2 main sections. Section A captured the demographics of the respondents, while Section B captured information on the constructs that aided in addressing the objectives of the study.

The study's target population was 680 final-year Bachelor of Science in Information Technology Management (BSc ITM) students at UPSA. The researchers employed purposive sampling to elicit data from the respondents. The respondents were assured of the confidentiality of the responses that they provided. The sample size was calculated using apriori sample test calculator statistical software, and the results indicated that a minimum of two hundred (200) respondents was needed for an effect size of 0.3, a desired statistical power level of 0.8, and a 5% probability level. An online questionnaire was used to collect data from the respondents.

Over 400 online questionnaires were distributed, but only 260 responses were received. The data that were received from the respondents were screened and cases that users' responses did not vary were deleted from the entire questionnaire. The final useful responses were 249, which is more than the minimum number of responses required.

Data analysis

Because there were multiple constructs and relationships, the researchers employed structural equation modeling for the analysis. The study employed a partial least square approach. The SMARTPLS 4 was used for the analysis. According to Hair *et al*. (2021), the analysis of PLS-SEM includes a two-stage approach. The first approach is to assess the measurement model, while the second stage appraises the structural model. The measurement model assesses how the items best describe the construct in question. The researchers assessed the measurement model by investigating the validity and reliability of the items. In this study, the researchers used factor loadings and average variance extracted (AVE) to measure internal consistency; Fornell-Lacker (1981). Heterotrait-Monotrrait ratio criteria were used to assess discriminant validity (Hensler *et al*., 2015). We also used Cronbach's alpha and composite reliability to assess the reliability.

Structural model appraisal

The structural model appraisal deals with the relationships between the constructs in the model. To appraise the structural model, according to Hair *et al*. (2021), we assessed it for collinearity issues. The study uses the Variance Inflation Factor (VIP) to measure collinearity among the set of predictor constructs. Furthermore, the study assessed the significance and relevance of the structural model relationships. The study addressed this issue by employing the bootstrapping process in PLS-SEM to assess the significance and relevance of path coefficients. Additionally, the study appraised the model's explanatory power by investigating the coefficient of determination (R^2), to understand how the exogenous constructs explain the endogenous constructs and the corresponding effect size (f^2) of each exogenous construct on the endogenous constructs.

Results

Demographics

The age distribution of the respondents as outlined in Table 1 is as follows: 24 (9.6%) were under the age of 18, 200 (80.3%) were between the ages of 19 and 25, 16 (6.4%) were between the ages of 26 and 30, 3 (1.2%) were between the ages of 31 and 40, and 6 (2.4%) were above 40. The age distribution indicates that the respondents were young, with the majority (90.9%) being under the age of 26. Females make up 114 (45.8%) of the responders, while males make

Table 1: Demographics

Variables	*Levels*	*Frequency (n)*	*Percentage (%)*
Age	Below 18	24	9.6
	19–25	200	80.3
	26–30	16	6.4
	31–40	3	1.2
	Above 40	6	2.4
Gender	Male	135	54.2
	Female	114	45.8

up 135 (54.2%). The results reveal that male users were more eager to participate in the study and have been transacting using Chat GPT.

Measurements Appraisal

The study presents the measurement appraisal result in Table 2. The factor loadings of CONF3 and CTRL2 factor loadings were removed from the model because their presence affects the validity and reliability of the model. The factor loadings exceed the desirable threshold of 0.708. The lowest factor loading is 0.803 and the highest is 0.941. The entire range of values for the average variance extracted (AVE) exceeds the threshold of 0.500. Although the Cronbach alpha value for EXP is 0.506 which is lower than the threshold, the entire Cronbach alpha and the composite reliability values exceed the 0.700 benchmark.

With regards to the discriminant validity, the results shown in Table 3 support both Henseler *et al*. (2015) and Fornell-Lacker (1981) evaluation criteria. The HTMT results with all values below 0.850 and confidence interval values do not include 1 (Table 3). Having established the validity and reliability of the model, the researcher then presents the results for the structural model appraisal.

Table 2: Convergent validity and internal consistency

Constructs	*Items*	*Convergent validity*		*Internal consistency*		
		Factor Loadings	*AVE*	*Cronbach's alpha*	*Composite reliability (rho_a)*	*Composite reliability (rho_c)*
CONF	CONF1.	0.941	0.876	0.859	0.862	0.934
	CONF2.	0.931				
CONV	CONV1	0.855	0.775	0.855	0.864	0.912
	CONV2	0.878				
	CONV3	0.907				
CTRL	CTRL1	0.929	0.849	0.823	0.828	0.918
	CTRL3	0.914				
ENJ	ENJ1.	0.803	0.669	0.506	0.508	0.802
	ENJ2.	0.832				
IDTY	IDTY1.	0.784	0.721	0.807	0.834	0.885
	IDTY2.	0.857				
	IDTY3.	0.902				
SAT	SAT1.	0.886	0.775	0.855	0.861	0.912
	SAT2.	0.878				
	SAT3.	0.877				
USE	USE1.	0.855	0.736	0.821	0.826	0.893
	USE2.	0.867				
	USE3.	0.852				

Table 3: Discriminant validity

Heterotraite-monotraite							*Fornell-Lacker*							
	CONF	*CONV*	*CTRL*	*ENJ*	*IDTY*	*SAT*		*CONF*	*CONV*	*CTRL*	*ENJ*	*IDTY*	*SAT*	*USE*
CONF							CONF	0.936						
CONV	0.621						CONV	0.533	**0.880**					
CTRL	0.781	0.707					CTRL	0.657	0.594	**0.921**				
ENJ	0.746	0.838	0.766				ENJ	0.491	0.551	0.49	**0.818**			
IDTY	0.614	0.568	0.538	0.835			IDTY	0.518	0.476	0.443	0.529	**0.849**		
SAT	0.741	0.673	0.742	0.819	0.565		SAT	0.64	0.582	0.627	0.543	0.478	**0.88**	
USE	0.656	0.6	0.698	0.756	0.528	0.696	USE	0.552	0.505	0.573	0.489	0.441	0.59	**0.858**

Table 4: Structural s

	Original sample (O)	*Sample mean (M)*	*Standard deviation (STDEV)*	*T statistics (|O/STDEV|)*	*P values*	R^2	f^2	*VIF*	*Interpretation*
CONF -> SAT (H1)	0.285	0.285	0.077	3.726	0		0.087	2.05	Accepted
CONV -> SAT (H2)	0.177	0.176	0.075	2.355	0.019	0.546	0.037	1.872	Accepted
CTRL -> SAT (H4)	0.23	0.227	0.077	2.983	0.003		0.055	2.093	Accepted
ENJ -> SAT (H5)	0.162	0.163	0.063	2.562	0.01		0.034	1.726	Accepted
IDTY -> SAT (H3)	0.058	0.065	0.062	0.944	0.345		0.005	1.62	Rejected
SAT -> USE (H6)	0.59	0.591	0.066	8.994	0	0.348	0.533	1	Accepted

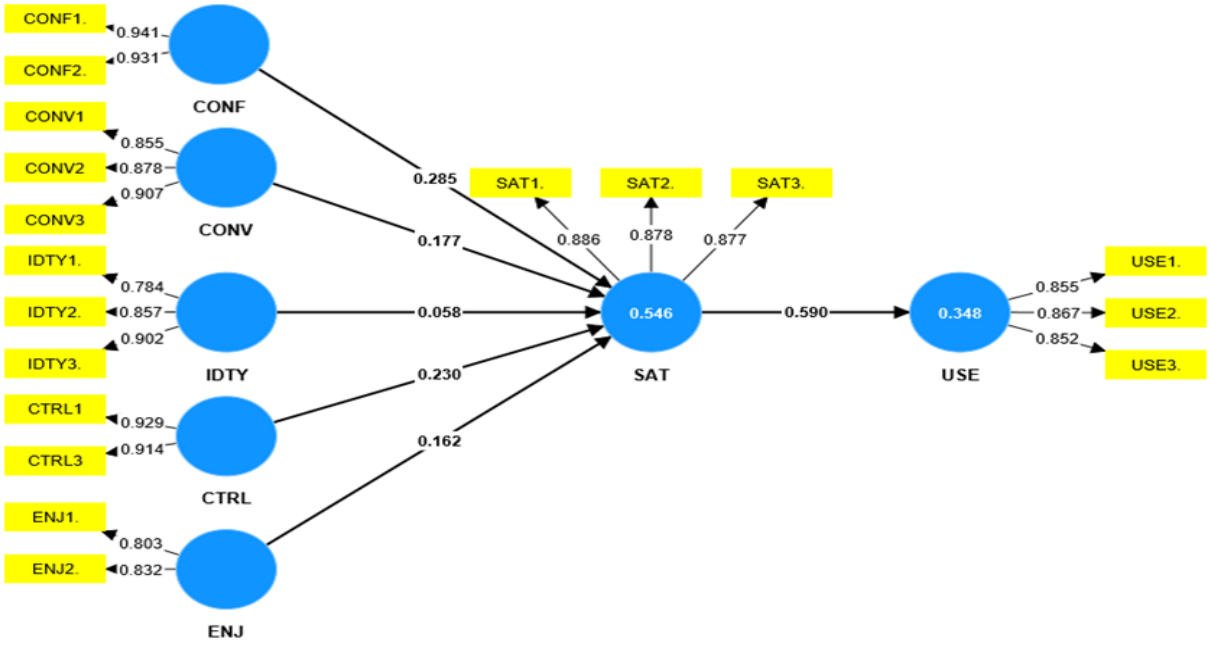

Figure 2: Path analysis

Structural Model Results

Table 4 presents the path coefficients in the t-values, p-values, and the confidence interval. Furthermore, Table 4 presents the coefficient of determination (R^2) and the corresponding effect sizes (f^2). Lastly, Table 4 includes variance inflation factor (VIF) values. The VIF values are below the 0.5 threshold (Hair *et al*., 2022). They range from 1.566 to 2.358. This suggests that there is no collinearity issue among the predictor constructs. The model's predictive power is measured by the coefficient of determination. The variance explained by the endogenous variables, SAT is 56.9%, and USE is 37.3%. The structural model demonstrates satisfactory predictive power, and the effect sizes, as shown in Table 4, range from 0.005 to 0.099 on SAT and 0.595 on USE.

Table 4 presents the standardized path coefficients, the p-values, and the t-values after the bootstrapping procedure of 5000 subsamples. The findings showed that apart from the relationship between IDTY and SAT (H3), all other hypotheses were supported at a 5% significant level. Again, Figure 2 presents the path diagram, which portrays similar information in Table 4.

Discussion

This research explored the antecedents of the use of AI chatbots among students in Ghana. We focused on Chat GPT, a type of AI chatbot, to investigate the determinants of AI chatbot usage among students in Ghana. This research was motivated by an inadequate understanding of the motivational and behavioral antecedents of actual use behavior concerning AI chatbots among students in low and middle-income countries. Considering the significant role AI chatbots play in enhancing information access and learning, it becomes essential to comprehend the determinants of actual usage of this digital innovation. Our study integrated UGT and SCT to bridge these knowledge gaps in the literature.

The findings of the study suggest that students' confidence in AI chatbots significantly influenced satisfaction, which supports H1. This can be attributed to students' consistent use of AI chatbots with limited issues and few lingering uncertainties or reservations about the service. The results corroborate the work of Özkan *et al*. (2019). In the context of low and middle-income countries, the relationship can be explained by the fact that the confidence factor increases positive feelings toward AI chatbots, which reduces the negative gap between expectations and perceptions. In addition, registering for AI chatbot services is not frustrating, and students can navigate such platforms without the need for high digital skills. Such service attributes of AI chatbots increase students' satisfaction.

Consistent with prior studies (e.g., Sari & Alfansi, 2024), this study revealed that convenience has a significant effect on students' satisfaction with AI chatbots supporting H2. This is understandable given that students in low and middle-income countries can conveniently access relatively affordable learning resources using AI chatbots, regardless of location and time. Such convenience will increase students' satisfaction. Similarly, the study suggests that control significantly affects users' satisfaction with AI chatbots and support H4. This result is consistent with prior studies (Ashfaq *et al*., 2020). This implies that AI chatbot features such as round-the-clock access, mobile-friendly or web accessibility options, and flexible scheduling empower students and give them personal control, increasing their satisfaction. In the same vein, findings show that enjoyment has a positive significant effect on students' AI chatbot satisfaction (H5), a result consistent with prior research (Huang *et al*., 2024). This implies that AI chatbots provide visually appealing interfaces, interactive content, and flexible as well as convenient access, making students' experiences more pleasurable and increasing their satisfaction. Furthermore, the findings of the study suggest that satisfaction has a significant effect on AI chatbot usage (H6). This suggests that students perceive AI chatbots as convenient, enjoyable, and secure, which motivates them to integrate AI chatbots into their daily lives and engage with it regularly. This finding aligns with Alnaser *et al*. (2023).

On the contrary, the findings of the study suggest that identity has an insignificant effect on students' satisfaction with AI chatbots. This does not support H3. The results are inconsistent with those of previous research conducted (Edwards *et al*., 2019). This implies that students do not necessarily feel like members of social, generational, or digital groups who are competent in the area of technology use when they use AI chatbots. Thus, we can infer from the findings that identity does not matter in AI chatbot usage among students in low and middle-income countries. Given that AI chatbots entail access to learning resources, it is probable that the decision to utilize AI chatbots is driven by the needs of students.

Theoretical implication

This study makes the following theoretical contributions. First, the use of UGT as a theoretical framework to investigate AI chatbot adoption among students in Ghana is scarce. Hence, our research expands the applicability of UGT in examining the use of AI chatbot adoption among students. While some existing studies have used UGT to investigate technology adoption in general, the application of this theory in the context of AI chatbots among students has been limited prior to this study.

Second, we adopt an integrated theoretical approach by combining UGT with SCT to enhance our understanding of the determinants of AI chatbot adoption among students in low and middle-income countries. Consequently, our study proffers novel insights by presenting a thorough evaluation of AI chatbot satisfaction and actual use behavior among students in Ghana. Through this unique approach, our study demonstrates how satisfaction influences actual usage with regard to AI chatbots among students. Considering the fact that the technology acceptance model primarily dominates existing studies in AI chatbot adoption literature, our study proffers novel insights that stimulate alternative discussions on the determinants of the use of AI chatbots among students. Hence, our study serves as a valuable basis for further studies.

Conclusion and limitations

This study sought to investigate the determinants that influence the actual use of AI chatbots among students in Ghana by integrating UGT and SCT, resulting in the development of a unique model. This study represents the first endeavor, to the best of our knowledge, to combine UGT and SCT within the AI chatbot domain. The results suggest that confidence, convenience, control, and enjoyment significantly affect students' AI chatbot satisfaction. Also, satisfaction affects the actual usage of AI chatbots among students in Ghana. Furthermore, some findings of our study diverge from previous research by revealing that identity does not significantly affect satisfaction. These findings enhance our understanding of the antecedents to the actual use of AI chatbots among students in low and middle-income countries.

This study is not without limitations. First, we focused on students at the University of Professional Studies in Ghana, which is considered a low and middle-income country. As a result, our findings may not necessarily apply to high-income countries. Also, we focused on students. Given that the AI chatbot ecosystem is vast, with key actors such as developers, faculty, administrators, and top management, it will be beneficial to also investigate the perceptions and experiences of these actors. Hence, future studies can

investigate the perceptions and viewpoints of these actors to have a better understanding of the AI chatbot ecosystem in educational settings.

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Supplementary Data

We are conducting a study on students' adoption of artificial intelligence (AI) chatbots using social cognitive theory and uses and gratification theory. This research seeks to investigate the factors that influence students' satisfaction with AI chatbots and ultimately determine usage. Your participation in this study is entirely voluntary. Participants' confidentiality and anonymity will not be compromised. The questionnaire will take approximately 5 minutes to complete. Thank you very much

Section A

Demographic characteristics

Please provide the following information:

Gender:

☐ Male ☐ Female ☐ Other

Age:

☐ Below 18 ☐ 19-25 ☐ 26-30 ☐ 31-40 ☐ 41 and above

Education Level:

☐ High School ☐ Diploma ☐ Bachelor's Degree ☐

Section B

This research seeks to investigate the factors that influence students' satisfaction with AI chatbots, particularly Chat GPT. Please indicate your level of agreement with the questions by indicating or selecting the following:

1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Constructs	*Items*	*Questions*	*Source*
Confidence	CONF1	I feel confident in my ability to use the AI chatbot	Qaisi and Alrosan (2020)
	CONF2	I can troubleshoot minor issues when using the AI chatbot without any help.	
	CONF3	I feel comfortable making decisions based on the generate data from the AI chatbot	
Convenience	CONV1	The AI chatbot makes learning more efficient.	Kurniawan et al. (2019)
	CONV2	The AI chatbot reduces paperwork and makes information retrieval easier.	
	CONV3	Using the AI chatbot helps me access information anytime, anywhere	
Identity	IDTY1	Using the AI chatbot makes me feel privileged.	Chowdhury et al. (2014)
	IDTY2	Using the AI chatbot gives me a sense of belonging in the modern digital world.	
	IDTY3	I feel part of the global tech-savvy community when using the AI chatbot	
Personal control	CNTRL1	AI chatbot gives me better control when accessing information	Zhu et al. (2016)
	CNTRL2	I can easily refine and modify search prompts on the AI chatbot.	
	CNTRL3	I feel empowered when using the AI chatbot to access educational content	
Enjoyment	ENJ1	Using AI chatbot for my studies is interesting and engaging.	Bae et al. (2020)
	ENJ2	I feel excited when exploring with the AI chatbot.	
	ENJ3	I enjoy using the AI chatbot to learn	
Satisfaction	SAT1	I am pleased to use the AI chatbot to as a learning tool	Tam et al. (2020)
	SAT2	I am pleased with the variety of information resources accessible via AI chatbot	
	SAT3	The AI chatbot meets my learning needs	
Use	USE1	I use the AI chatbot frequently	Venkatesh et al. (2012)
	USE2	I use the AI chatbot a lot	
	USE3	I use the AI chatbot daily	