An Integrated Model of ChatGPT Acceptance and Continuance in Cambodian Higher Education

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ABSTRACT:

This study examines an integrated model of ChatGPT acceptance and continuance among Cambodian undergraduate students by combining UTAUT constructs, including performance expectancy, effort expectancy, social influence, and facilitating conditions, with expectation confirmation and satisfaction. Data were collected from 421 students across seven public and private universities in Phnom Penh, Cambodia using a structured online survey and analyzed through PLS-SEM. Findings reveal that social influence and satisfaction significantly drive students' behavioral intention, while confirmation strongly affects both performance expectancy and satisfaction. Facilitating conditions and behavioral intention positively influence actual use behavior, highlighting the importance of both structural support and motivational factors. The study contributes to theory by integrating acceptance and post-adoption perspectives, offers empirical evidence from a developing higher education context, and provides insights for designing effective strategies to promote responsible and sustained engagement with generative AI in undergraduate learning.

Keywords: Generative AI, UTAUT, technology acceptance, student satisfaction, Cambodian universities.

1. Introduction

The rapid advancement of generative artificial intelligence (AI) has introduced transformative possibilities for higher education, reshaping how students access information, complete academic tasks, and engage in learning processes. Among these innovations, ChatGPT has emerged as one of the most widely adopted AI tools, capable of generating human like responses, supporting writing and problem solving tasks, and facilitating personalized learning experiences (Adiguzel et al., 2023; Chanpradit, 2025; Michel-Villarreal et al., 2023). As universities increasingly experiment with integrating ChatGPT into teaching and learning activities, understanding the factors that drive students' acceptance, continued use, and actual utilization of such technologies has become a critical research priority.

Existing studies suggest that ChatGPT offers substantial educational benefits, including enhanced student productivity, improved learning support, and opportunities for higher order thinking development (Fauzi et al., 2023; Kayalı et al., 2023; Wang et al., 2025). At the same time, concerns related to academic integrity, ethical use, overreliance, and misuse have raised important

pedagogical and policy questions (Cotton et al., 2024; Farhi et al., 2023; Megahed et al., 2024). These mixed perceptions underscore the necessity of moving beyond descriptive evaluations of ChatGPT's potential and toward theory driven empirical models that explain not only initial adoption but also sustained and meaningful use in higher education contexts.

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been widely applied to explain individuals' behavioral intention and use behavior of emerging technologies in educational settings (Hakimi et al., 2024; Venkatesh et al., 2003). Core UTAUT constructs including performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) have

. In the context of ChatGPT, students may initially adopt the tool due to perceived usefulness or ease of use, but sustained use is more likely to depend on whether the system confirms their expectations and delivers satisfactory academic outcomes (Chan & Hu, 2023; Chen et al., 2023). Despite growing interest in this integrated perspective, empirical studies that simultaneously examine technology acceptance and continuance of ChatGPT use remain limited, particularly within developing higher education systems.

This gap is especially evident in the Cambodian higher education context. While recent conceptual and qualitative work highlights the transformative potential of ChatGPT for Cambodian education (Huot & Loch, 2025; Islam, 2024), empirical evidence on undergraduate students' behavioral intention and actual use behavior remains scarce. Cambodian universities encounter a range of contextual challenges associated with limited digital infrastructure, variations in institutional support, evolving pedagogical approaches, and differences in students' capacity for self-regulation. In addition, emerging work on generative AI literacy highlights the importance of ethical awareness, user engagement, and competence in shaping responsible AI use in higher education settings (Kwon, 2024). Prior research indicates that faculty development practices, curriculum design, and learning environments play a critical role in shaping student learning outcomes in Cambodian higher consistently demonstrated strong explanatory power in predicting students' intentions to adopt digital learning technologies, including AI based systems (Maisha & Shetu, 2023; Miah et al., 2023; Rana et al., 2024; Yakubu et al., 2025). However, recent literature highlights a key limitation of UTAUT based studies. Most focus primarily on initial acceptance and overlook post adoption processes such as satisfaction, confirmation of expectations, and continuance behavior (Baig & Yadegaridehkordi, 2024; Feng & Haridas, 2025).

To address this limitation, scholars increasingly advocate integrating UTAUT with the Expectation Confirmation Model, which emphasizes users' post use evaluations, satisfaction, and continuance intention (Baig & Yadegaridehkordi, 2024)

education (Holl & Ali, 2025; Lork et al., 2025; Lork & Ali, 2025). These structural and pedagogical conditions are likely to influence how technology acceptance factors and post adoption mechanisms function within this context, thereby constraining the direct transferability of findings derived from studies conducted in more technologically advanced higher education systems.

Furthermore, most existing generative AI studies in higher education rely on cross sectional perceptions or exploratory designs, offering limited insight into how intention translates into actual use behavior (Lo, 2023; Singh et al., 2023). There is a clear need for robust empirical models that explain not only why students intend to use ChatGPT but also how and why they continue to use it in practice. Integrating confirmation and satisfaction into the UTAUT framework provides a more comprehensive explanation of students' post adoption behavior and aligns with recent calls for deeper theoretical integration in AI adoption research (Feng & Haridas, 2025; Rana et al., 2024).

Against this backdrop, the present study aims to test an integrated model of technology acceptance and continuance of ChatGPT use among Cambodian undergraduate students. By combining UTAUT constructs including performance expectancy, effort expectancy, social influence, and facilitating conditions with expectation confirmation and satisfaction, this study seeks to explain both

behavioral intention and actual use behavior of ChatGPT in higher education. Empirically, the study contributes novel evidence from Cambodia, an under researched developing country context, thereby extending the external validity of existing AI adoption models. Theoretically, it advances the literature by demonstrating how acceptance and continuance mechanisms jointly shape students' engagement with generative AI technologies. Practically, the findings offer actionable insights for policymakers, university administrators, and educators seeking to design effective strategies for the responsible and sustainable integration of ChatGPT into undergraduate education.

Emergence of Generative AI in Higher Education

Generative AI has become increasingly prominent within higher education, with ChatGPT emerging as one of the most transformative technologies in recent years. Existing scholarship characterizes ChatGPT as an advanced conversational tool that can support a wide range of academic activities, including academic writing assistance, problem solving, information retrieval, and the facilitation of personalized learning experiences (Adarkwah et al., 2023; Kasneci et al., 2023; Michel-Villarreal et al., 2023) Empirical studies conducted across various educational settings indicate that, when effectively integrated into learning processes, ChatGPT may contribute positively to student productivity, learning efficiency, and academic engagement (Baek et al., 2024; Fauzi et al., 2023; Firaina & Sulisworo, 2023).

However, researchers consistently caution that the educational benefits of ChatGPT are not inherent but are shaped by contextual and pedagogical factors. Specifically, institutional regulations, instructional design strategies, and students' ability to use the technology responsibly and critically play a decisive role in determining learning outcomes (Farrokhnia et al., 2024; Zeb et al., 2024). Without appropriate guidance and governance, the use of generative AI tools may raise concerns related to academic integrity, overreliance, and superficial learning.

Furthermore, evidence from systematic reviews suggests that much of the initial research on ChatGPT in higher education has concentrated on conceptual analyses, ethical debates, and descriptive examinations of user perceptions and attitudes (Baig & Yadegaridehkordi, 2024; Lo, 2023; Montenegro-Rueda et al., 2023). Although these studies offer important foundational insights into the opportunities and limitations associated with generative AI, they provide limited empirical understanding of the underlying behavioral mechanisms that influence students' continued intention to use and actual use of ChatGPT for academic learning purposes.

Student Perceptions and Attitudes Toward ChatGPT

An expanding stream of empirical research has investigated university students' perceptions, attitudes, and levels of awareness regarding the use of ChatGPT in higher education. Evidence from studies conducted across varied regional contexts, including Jordan, Ghana, China, and several European countries, indicates that students generally demonstrate favorable attitudes toward ChatGPT as a supplementary learning tool. These positive evaluations are largely attributed to its perceived usefulness, ease of access, and ability to provide immediate academic support (Adarkwah et al., 2023; Ajlouni et al., 2023; Moradi, 2025). Students commonly perceive ChatGPT as beneficial for generating ideas, clarifying complex academic concepts, and assisting with academic writing and coursework preparation (Chan & Hu, 2023; Miah et al., 2023; Valeri et al., 2025).

Despite these perceived benefits, empirical findings also consistently document significant concerns that influence students' engagement with generative AI technologies. In particular, issues related to academic integrity, the accuracy and credibility of AI generated content, and the risk of excessive reliance on automated tools remain prominent (Cotton et al., 2024; Farhi et al., 2023; Megahed et al., 2024). Such apprehensions contribute to more cautious and selective patterns of use among students and underscore the complexity of ChatGPT adoption in academic contexts. Consequently, existing research highlights the

importance of moving beyond initial acceptance and intention to adopt, toward a deeper examination of actual use behavior and post adoption evaluation processes that shape sustained and responsible use of ChatGPT in higher education learning environments.

Technology Acceptance Models in ChatGPT Research

Technology acceptance frameworks have been extensively employed to explain students' adoption, intention, and actual use of ChatGPT in higher education. Among these frameworks, the UTAUT and its extensions have emerged as the most widely applied models, providing a structured lens through which to understand the determinants of student engagement with generative AI tools (Duong et al., 2023; Menon & Shilpa, 2023; Yakubu et al., 2025). Empirical evidence consistently identifies performance expectancy as one of the most influential predictors of students' behavioral intention to adopt ChatGPT. This construct reflects the extent to which students believe that using the tool will improve their academic performance, enhance learning outcomes, and facilitate completion of academic tasks more efficiently (Kumar Tiwari et al., 2024; Mansoor Siddiqui et al., 2025). High performance expectancy thus encourages proactive engagement with ChatGPT as a supplementary educational resource.

Effort expectancy also plays a critical role, particularly during the initial stages of technology adoption. Students are more inclined to use ChatGPT when the interface is intuitive, easy to navigate, and does not require extensive prior knowledge or technical skills (Albayati, 2024; Ma et al., 2025). In addition, social influence is a context-dependent factor that can shape students' adoption behavior. Peer recommendations, instructor encouragement, and prevailing institutional norms significantly affect the acceptance of ChatGPT, especially in learning environments characterized by collectivist values or instructor-guided pedagogy environments (Owan et al., 2025; Strzelecki et al., 2024). Facilitating conditions, which encompass the availability of technological resources, reliable internet connectivity, and institutional support, have been found to exert a stronger impact on actual use behavior rather than on behavioral intention alone (Alshammari & Alshammari, 2024; Matsiola et al., 2025). Together, these factors highlight that students' adoption and continued use of ChatGPT is influenced by a combination of perceived usefulness, ease of use, social and institutional contexts, and practical support mechanisms, underscoring the relevance of integrating UTAUT constructs with post-adoption and continuance models to fully understand engagement with generative AI in higher education.

Beyond Adoption Intention: Continuance, Confirmation, and Satisfaction

While studies based on the UTAUT provide substantial insight into the factors influencing initial adoption of ChatGPT, emerging research highlights the importance of considering post adoption constructs, particularly confirmation and satisfaction, to better understand sustained usage behavior (Polyportis, 2023; Polyportis & Pahos, 2025). Expectation confirmation theory suggests that continued engagement with a technology is contingent upon the degree to which users perceive that its actual performance aligns with or surpasses their initial expectations. When this alignment occurs, users experience satisfaction, which fosters ongoing commitment and habitual use.

Empirical evidence demonstrates that students who achieve favorable learning outcomes and perceive ChatGPT as a reliable and effective academic tool are more likely to report high levels of satisfaction, which subsequently reinforces their intention to continue using the technology (Ligorio & Rashid, 2025; Niloy et al., 2024). Satisfaction, therefore, acts as a critical mediator linking perceived utility and actual use behavior over time. Conversely, when students encounter discrepancies between expectations and actual performance, such as inaccuracies in AI-generated content, ethical dilemmas, or inappropriate application in assessments, satisfaction diminishes, potentially undermining their willingness to engage with ChatGPT in the long term (Farrokhnia et al., 2024; Valova et al., 2024). Despite the increasing recognition of these dynamics, a notable gap remains in integrating expectation confirmation and satisfaction with UTAUT constructs in the context

of generative AI adoption in higher education. Addressing this gap is essential for developing a more comprehensive understanding of both initial adoption and continued use behaviors, providing theoretical advancement and practical guidance for the sustainable integration of ChatGPT in academic settings.

Contextual Influences and Evidence from Developing Higher Education Systems

Contextual factors are widely recognized as critical determinants of technology acceptance and continued use in educational settings. Research conducted in developing countries highlights the role of institutional readiness, curriculum alignment, and pedagogical support in shaping students' engagement with AI-based learning tools (Maisha & Shetu, 2023; Rana et al., 2024). In environments characterized by limited digital infrastructure or uneven faculty support, these contextual variables may moderate the relationships between UTAUT constructs and students' behavioral intentions or actual use behaviors. Evidence from Southeast Asia and comparable educational systems further indicates that students' self-regulation skills, the design of instructional activities, and institutional policies substantially influence how AI technologies are adopted and utilized for learning purposes (Huot & Loch, 2025; Lork & Ali, 2025). These factors underscore that the efficacy of AI tools like ChatGPT is not determined solely by their inherent functionalities, but also by the surrounding learning environment and support mechanisms that guide responsible and effective use.

Despite these insights, empirical research examining AI adoption and continued use among Cambodian undergraduate students remains limited. In particular, studies that integrate technology acceptance frameworks with post-adoption variables such as confirmation and satisfaction are scarce. This gap points to the need for context-specific investigations that account for both individual and institutional factors, providing a more comprehensive understanding of students' engagement with generative AI in Cambodian higher education.

Research Gap and Conceptual Direction

In summary, existing literature demonstrates that ChatGPT adoption in higher education is influenced by a combination of technological, social, and institutional factors. While UTAUT based models effectively explain students' behavioral intention, they offer limited insight into post adoption processes such as satisfaction and confirmation that drive sustained use. Moreover, most empirical studies are conducted in developed or technologically advanced contexts, limiting their applicability to developing higher education systems.

Therefore, there is a clear need for empirical research that integrates UTAUT constructs with expectation confirmation and satisfaction to explain both behavioral intention and actual use behavior of ChatGPT among undergraduate students in Cambodia. Addressing this gap will contribute to theoretical advancement by linking acceptance and continuance perspectives and provide practical guidance for the sustainable integration of generative AI in higher education.

Hypotheses and Conceptual Framework

H1: Performance expectancy has a positive effect on students' behavioral intention to use ChatGPT.

H2: Effort expectancy has a positive effect on students' behavioral intention to use ChatGPT.

H3: Social influence has a positive effect on students' behavioral intention to use ChatGPT.

H4: Facilitating conditions have a positive effect on students' behavioral intention to use ChatGPT.

H5: Students' satisfaction positively influences their behavioral intention to continue using ChatGPT.

H6: Confirmation positively influences students' performance expectancy regarding the use of ChatGPT.

H7: Confirmation positively influences students' satisfaction with the use of ChatGPT.

H8: Performance expectancy positively influences students' satisfaction with the use of ChatGPT.

H9: Facilitating conditions have a positive effect on students' actual use behavior of ChatGPT.

H10: Behavioral intention has a positive effect on students' actual use behavior of ChatGPT.

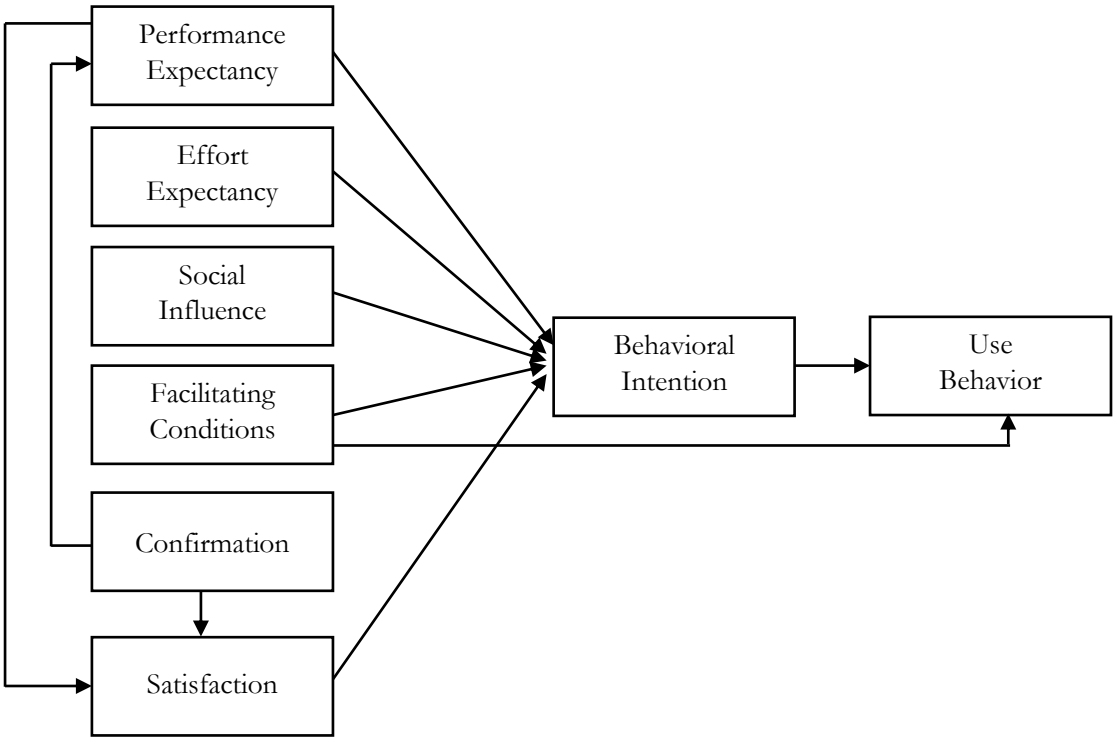

Figure 1: Conceptual Framework

2. Methodology

This research is grounded in a positivist philosophical approach, based on the view that reality exists independently and can be examined through observable and measurable facts. The positivist perspective emphasizes the use of numerical data and systematic data collection methods to evaluate hypotheses and draw objective conclusions. As a result, surveys and statistical techniques are commonly employed to analyze the phenomena under investigation (Ahmed, 2024; Hossan et al., 2023). This study follows a deductive reasoning process, starting from established theories and previous empirical findings to develop testable hypotheses. These hypotheses are subsequently examined using empirical data, reflecting a movement from broad theoretical concepts to specific observations, which aligns well with structured quantitative research designs (NKK Gamage, 2025).

The study adopts a quantitative methodology, focusing on the collection of numerical data and its analysis through statistical techniques. This approach supports objective hypothesis testing and enables the measurement of relationships among variables through standardized tools such as questionnaires and surveys (Mahardini et al., 2024). A survey strategy is utilized to systematically gather structured data from respondents, facilitating pattern identification and the generation of dependable conclusions. In addition, a cross-sectional research design is employed, with data collected at a single point in time to explore relationships between variables without the need for longitudinal observation (Ahmed, 2024).

A survey method was chosen as the primary research strategy due to its suitability for collecting data from a large number of respondents within a limited timeframe. The data were gathered in Phnom Penh, Cambodia, from 1 to 31 September 2025 using a self-administered online questionnaire developed for quantitative analysis. This approach supports the generation of results that can be generalized to the target population. The questionnaire was created using Google Forms and distributed through Telegram student groups, focusing on second- and fourth-year students from seven higher education institutions, including both public and private universities. The development and distribution of the survey were overseen by the research team under the supervision of the lead author to ensure consistency and the reliability of the collected data (Ahmed, 2024; Hossan et al., 2023).

Due to the lack of reliable population data, the study employed a non-probability sampling method to secure an adequate number of responses for statistical analysis. This approach is commonly used in quantitative research when a complete sampling frame is not available and practical constraints make probability sampling difficult to implement (Mukti, 2025). While non-probability sampling allows researchers to reach accessible and willing participants, it also restricts the extent to which findings can be generalized (Elfil & Negida, 2017). Participants were selected using convenience sampling, targeting students who were readily available and willing to participate (Mukti, 2025). To enhance representation, quota sampling was applied within each institution to ensure the inclusion of students from different academic disciplines and year levels. This involved setting target numbers for specific subgroups and continuing data collection until those targets were achieved, often alongside convenience techniques (Elfil & Negida, 2017).

In total, approximately 600 respondents were targeted, with around 100 participants from each university. All participants were informed about the purpose of the study, assured of confidentiality, and participated voluntarily. Although this sampling strategy does not provide equal selection opportunities for all students, it is appropriate for structured quantitative studies conducted in settings where population data are limited but input from diverse student groups is required (Ahmed, 2024; Hossan et al., 2023; Mukti, 2025). Data were gathered using an online questionnaire designed through Google Forms, with all questions marked as mandatory to limit incomplete or invalid submissions. As is typical in online survey studies, not all individuals who received the link completed the questionnaire. After the data screening process, 421 valid responses were retained from the 600 distributed surveys, resulting in a response rate of approximately 70.2%. This degree of non-response is commonly observed in self-administered online surveys and is generally considered acceptable, provided that the final sample size remains sufficient for meaningful statistical analysis (Dillman et al., 2014; Nulty, 2008).

The measurement items for each construct were adapted from prior validated studies to support content validity. All items were assessed using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The constructs of performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and use behavior were each measured using four indicators, while confirmation and satisfaction were measured using five items each. In line with the UTAUT and ECM frameworks, performance expectancy, effort expectancy, social influence, and facilitating conditions were specified as independent variables. Behavioral intention and use behavior were treated as dependent variables. In addition, demographic data were collected through sixteen items covering characteristics such as age, gender, prior experience with ChatGPT, and voluntariness of use.

Data analysis was conducted using SPSS (version 26) and SmartPLS. SPSS was employed to generate descriptive statistics such as means, standard deviations, and correlation coefficients, and to assess sampling adequacy through the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's test of sphericity. The analytical process followed the two-stage approach proposed by Anderson and Gerbing (1988). The first stage focused on evaluating the measurement model, including tests of reliability,

internal consistency, and construct validity. The second stage involved hypothesis testing and the examination of structural relationships using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Structural Equation Modeling (SEM) is an advanced multivariate technique that enables the examination of complex relationships among latent constructs and their observed indicators, as well as among independent and dependent variables. Among SEM approaches, PLS-SEM is particularly appropriate for theory development or extension, especially in situations involving relatively small sample sizes, non-normal data distributions, or emerging theoretical frameworks (Hair et al., 2011; Raza et al., 2017). PLS-SEM has been widely applied in the social and behavioral sciences, including research in management, marketing, and psychology (Hair et al., 2012).

Previous studies have also documented methodological developments in PLS-SEM, such as procedures for testing moderating effects (Henseler & Fassott, 2010), guidelines for evaluating measurement models using confirmatory factor analysis (Hair et al., 2011), and methods for assessing predictive relevance and overall model quality (Hair et al., 2011; Pavlou & Fygenson, 2006). In addition, Reinartz et al. (2009) noted that PLS-SEM is well suited for analyzing complex models with multiple constructs. Moreover, PLS-SEM supports both reflective and formative measurement models, providing flexibility in evaluating measurement and structural components. Its application in this study allows for a comprehensive assessment of the proposed constructs and their relationships, thereby strengthening the interpretation and theoretical contribution of the findings.

3. Result

Demographic profile

Table 1 summarizes the demographic profile of the respondents (N = 421). The majority of participants were aged between 18 and 20 years (58.4%), followed by those aged 21–24 years (35.6%). Smaller proportions were under 18 years (3.1%), 25–29 years (2.4%), and over 30 years (0.5%). Regarding gender, most respondents were female (81.9%), while males accounted for 18.1% of the sample. In terms of experience with ChatGPT, 37.1% of respondents had 6–12 months of experience, 27.1% had 1–3 years, 24.7% had less than six months, 10% had no experience, and only 1.2% reported more than three years of usage. Overall, the sample reflects a young, predominantly female population with varied levels of experience using ChatGPT.

Table 1: The demographic profile

Factors	Classification	Repetition	Proportion
Age	<18yrs	13	3.1
	18-20yrs	246	58.4
	21-24yrs	150	35.6
	25-29yrs	10	2.4
	> 30yrs	2	0.5
Gender	Male	76	18.1
	Female	345	81.9
Experience with ChatGPT	No Experience	42	10.0
	Last than 6 months	104	24.7
	6-12 months	156	37.1
	1-3 years	114	27.1
	More than 3 years	5	1.2
N		***421***	

Descriptive and Correlation Matrix

All variables were positively and significantly correlated ($p < 0.01$), with behavioral intention strongly predicting use behavior ($r = 0.709$) and confirmation closely associated with satisfaction ($r = 0.742$). The results show moderate correlations among the perceived risk constructs and mobile banking use, with all coefficients below 0.85, indicating that multicollinearity is not a concern. Consequently, the data are deemed appropriate for PLS-SEM analysis (Kline, 2011).

Table 2**:** Mean, Standard Deviation and Correlations

	Mean	Std	PE	EE	SI	FC	BI	UB	CON	SAT
PE	3.377	0.766								
EE	3.291	0.767	0.637**							
SI	2.971	0.777	0.414**	0.433**						
FC	3.169	0.727	0.609**	0.628**	0.506**					
BI	3.052	0.718	0.466**	0.473**	0.592**	0.524**				
UB	2.943	0.772	0.446**	0.509**	0.591**	0.537**	0.709**			
CON	3.098	0.688	0.567**	0.591**	0.564**	0.656**	0.659**	0.688**		
SAT	3.2109	0.701	0.564**	0.586**	0.520**	0.655**	0.663**	0.697**	0.742**	

***. Correlation is significant at the 0.01 level (2-tailed)*

Std = Standard Deviation, PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions, BI = Behavioral Intention, UB = Use Behavior, CON = Confirmation, SAT = Satisfaction

Internal Consistency, Reliability, and Validity Testing

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.944, indicating excellent suitability of the data for factor analysis (Kaiser, 1974). Bartlett's test of sphericity was significant ($\chi^2 = 9{,}261.487$, $df = 561$, $p < 0.001$), confirming that correlations among items were sufficient for factor extraction. Principal Component Analysis (PCA) was conducted, and all items showed extraction communalities above 0.50, ranging from 0.565 to 0.749. These results indicate that each item shared a substantial portion of variance with its underlying construct, making them appropriate for inclusion in the analysis.

The reliability and convergent validity of the constructs were evaluated using factor loadings, Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE), based on the guidelines of Ramayah et al. (2017). All items had factor loadings above 0.70, while CA and CR values exceeded 0.70, and AVE values were higher than 0.60, indicating that the constructs were both reliable and valid. These findings confirm that the measurement model has satisfactory internal consistency and that the items effectively represent their intended constructs.

Table 3**:** Construct Reliability and Validity

Constructs	Items	Loadings	Cronbach Alpha	Composite Reliability	Average Variance Extracted
Behavioral Intention	BI1	0.788	0.835	0.890	0.669
	BI2	0.837			
	BI3	0.820			
	BI4	0.825			
Confirmation	CON1	0.784	0.879	0.912	0.674
	CON2	0.799			

Constructs	Items	Loadings	Cronbach Alpha	Composite Reliability	Average Variance Extracted
	CON3	0.839			
	CON4	0.860			
	CON5	0.820			
Effort Expectancy	EE1	0.780	0.852	0.900	0.692
	EE2	0.838			
	EE3	0.858			
	EE4	0.848			
Facilitating Conditions	FC1	0.836	0.832	0.888	0.664
	FC2	0.803			
	FC3	0.830			
	FC4	0.790			
Performance Expectancy	PE1	0.838	0.831	0.887	0.663
	PE2	0.796			
	PE3	0.800			
	PE4	0.822			
Satisfaction	SAT1	0.825	0.888	0.918	0.691
	SAT2	0.844			
	SAT3	0.839			
	SAT4	0.811			
	SAT5	0.837			
Social Influence	SI1	0.791	0.828	0.886	0.659
	SI2	0.835			
	SI3	0.806			
	SI4	0.815			
Use Behavior	UB1	0.837	0.844	0.895	0.680
	UB2	0.862			
	UB3	0.812			
	UB4	0.787			

Table 4 presents the correlations among latent constructs based on the Fornell-Larcker criterion. The diagonal values, representing the square root of each construct's AVE, are higher than the correlations with other constructs, indicating satisfactory discriminant validity. Most constructs showed moderate correlations. Behavioral Intention with Use Behavior (r = 0.712) and Effort Expectancy with Facilitating Conditions (r = 0.630) demonstrating meaningful relationships without multicollinearity concerns. Some constructs, such as Social Influence, exhibited lower correlations with other variables (ranging from 0.416 to 0.594), emphasizing their distinctiveness. Overall, these results confirm that all constructs meet the Fornell-Larcker criterion for discriminant validity, supporting the adequacy and reliability of the measurement model (Fornell & Larcker, 1981).

Table 4: Latent Variable Correlations (Fornel-Larcker Criterion)

Constructs	BI	CON	EE	FC	PE	SAT	SI	UB
Behavioral Intention (BI)	0.818							
Confirmation (CON)	0.658	0.821						
Effort Expectancy (EE)	0.479	0.591	0.832					
Facilitating Conditions (FC)	0.528	0.660	0.630	0.815				
Performance Expectancy (PE)	0.468	0.568	0.644	0.609	0.814			
Satisfaction (SAT)	0.664	0.744	0.591	0.658	0.568	0.831		
Social Influence (SI)	0.594	0.573	0.433	0.512	0.416	0.528	0.812	
Use Behavior (UB)	0.712	0.689	0.518	0.545	0.454	0.704	0.591	0.825

The Heterotrait-Monotrait (HTMT) ratio was used to further evaluate discriminant validity (Henseler et al., 2015). As shown in Table 5, all HTMT values were below the recommended threshold of 0.85, indicating that the constructs are sufficiently distinct. The highest value was observed between Behavioral Intention and Use Behavior (0.846), reflecting a moderate relationship while preserving construct uniqueness. Other constructs, including Social Influence, showed moderate HTMT values with the remaining constructs (0.500-0.712), further confirming their distinctiveness. These results align with the Fornell-Larcker criterion (Fornell & Larcker, 1981) and provide additional evidence that the measurement model is reliable and demonstrates satisfactory discriminant validity.

Table 5: Discriminant Validity (Heterotrait-Monotrait Ratio - HTMT)

Constructs	BI	CON	EE	FC	PE	SAT	SI	UB
Behavioral Intention (BI)								
Confirmation (CON)	0.768							
Effort Expectancy (EE)	0.563	0.682						
Facilitating Conditions (FC)	0.625	0.766	0.747					
Performance Expectancy (PE)	0.557	0.663	0.760	0.734				
Satisfaction (SAT)	0.768	0.840	0.676	0.758	0.655			
Social Influence (SI)	0.712	0.666	0.515	0.610	0.500	0.610		
Use Behavior (UB)	0.846	0.800	0.603	0.639	0.533	0.803	0.709	

Common Method Bias Assessment

Common method bias was assessed using the full collinearity approach recommended by Kock (2015). As shown in Table 6, all inner Variance Inflation Factor (VIF) values were well below the threshold of 3.3, ranging from 1.000 to 2.305. These results indicate that the structural model is not affected by common method bias and that multicollinearity among constructs is not a concern (Hair & Sarstedt, 2021; Kock, 2015). Therefore, the measurement and structural relationships can be interpreted with confidence, without the risk of inflated correlations caused by common method effects.

Table 6: Full Collinearity Assessment of Common Method Bias (VIF Values)

Constructs	BI	PE	SAT	UB
Behavioral Intention (BI)				1.387
Confirmation (CON)		1.000	1.476	
Effort Expectancy (EE)	2.305			
Facilitating Conditions (FC)	2.004			1.387

Constructs	BI	PE	SAT	UB
Performance Expectancy (PE)	2.135		1.476	
Satisfaction (SAT)	1.498			
Social Influence (SI)	2.120			
Use Behavior (UB)				

Structural Model Evaluation

The effect sizes (f^2) of the predictor constructs were examined to evaluate the strength of their influence on endogenous constructs (Cohen, 1988; Hair & Sarstedt, 2021). As presented in Table 7, Behavioral Intention had a large effect on Use Behavior (f^2 = 0.550), indicating it is a strong determinant. Confirmation showed substantial effects on Performance Expectancy (f^2 = 0.476) and Satisfaction (f^2 = 0.632). Social Influence demonstrated a medium effect on Behavioral Intention (f^2 = 0.141), while Effort Expectancy (f^2 = 0.001), Facilitating Conditions (f^2 = 0.087), and Performance Expectancy (f^2 = 0.076) exhibited small effects. These results suggest that although all predictors contribute to their respective dependent constructs, Behavioral Intention is the most influential factor driving Use Behavior. Overall, the findings support the robustness of the structural model and highlight the relative importance of each predictor in explaining user outcomes.

Table 7: Effect Size (f^2) of Predictor Constructs

Predictor Construct	BI	PE	SAT	UB	Effect Size
Behavioral Intention (BI)				0.550	Large
Confirmation (CON)		0.476	0.632		Medium/Large
Effort Expectancy (EE)	0.001				Small
Facilitating Conditions (FC)	0.001			0.087	Small
Performance Expectancy (PE)	0.003		0.076		Small
Satisfaction (SAT)	0.180				Medium
Social Influence (SI)	0.141				Medium

After validating the measurement model, the predictive power of the structural model was assessed using R^2 values, which indicate the proportion of variance in endogenous constructs explained by their predictors (Hair & Sarstedt, 2021). As shown in Table 8, Behavioral Intention had an R^2 of 0.529 (adjusted R^2 = 0.523), Performance Expectancy had an R^2 of 0.322 (adjusted R^2 = 0.321), Satisfaction had an R^2 of 0.585 (adjusted R^2 = 0.583), and Use Behavior had an R^2 of 0.546 (adjusted R^2 = 0.544). These results suggest that the model explains 32–58% of the variance in the endogenous constructs, reflecting moderate to substantial explanatory power and supporting the predictive capability of the proposed research framework.

Table 8: Coefficient of Determination (R Square)

Constructs	R-square	R-square adjusted
Behavioral Intention (BI)	0.529	0.523
Performance Expectancy (PE)	0.322	0.321
Satisfaction (SAT)	0.585	0.583
Use Behavior (UB)	0.546	0.544

The predictive relevance of the model was assessed using the blindfolding procedure, which produces Q^2 values for endogenous constructs. A Q^2 value greater than zero indicates adequate predictive accuracy (Hair & Sarstedt, 2021). As shown in Table 9, all endogenous constructs had Q^2 values above zero: Behavioral Intention (Q^2 = 0.346), Performance Expectancy (Q^2 = 0.209), Satisfaction (Q^2 = 0.399), and Use Behavior (Q^2 = 0.368). These results confirm that the model has sufficient predictive relevance, supporting its robustness and demonstrating both explanatory and predictive capability.

Table 9: Construct Cross Validated Redundancy (Q Square)

Constructs	SSE	SSO	1-SSE/SSO
Behavioral Intention (BI)	1,684.000	1,101.155	0.346
Performance Expectancy (PE)	1,684.000	1,331.847	0.209
Satisfaction (SAT)	2,105.000	1,264.210	0.399
Use Behavior (UB)	1,684.000	1,064.165	0.368

Note: *SSO - Systematic Sources of Output; SSE - Systematic Sources of Error*

The overall fit of the structural model was assessed using multiple goodness-of-fit (GoF) indices. As shown in Table 10, the Standardized Root Mean Square Residual (SRMR) for the estimated model was 0.092, which is below the recommended threshold of 0.10, indicating an acceptable fit between the model and the observed data (Henseler et al., 2016). The discrepancy measures, d_ULS (4.996) and d_G (0.969), further support the adequacy of the model. Additionally, the Chi-Square value (2,218.727) and Normed Fit Index (NFI = 0.767) suggest that the estimated model reasonably represents the data structure. Overall, these fit indices indicate that the proposed research model demonstrates a satisfactory fit, providing a reliable basis for interpreting the structural relationships.

Table 10: Goodness of Fit of The Model

Item	Saturated Model	Estimated Model
SRMR	0.058	0.092
d_ULS	1.978	4.996
d_G	0.829	0.969
Chi-Square	2,044.805	2,218.727
NFI	0.786	0.767

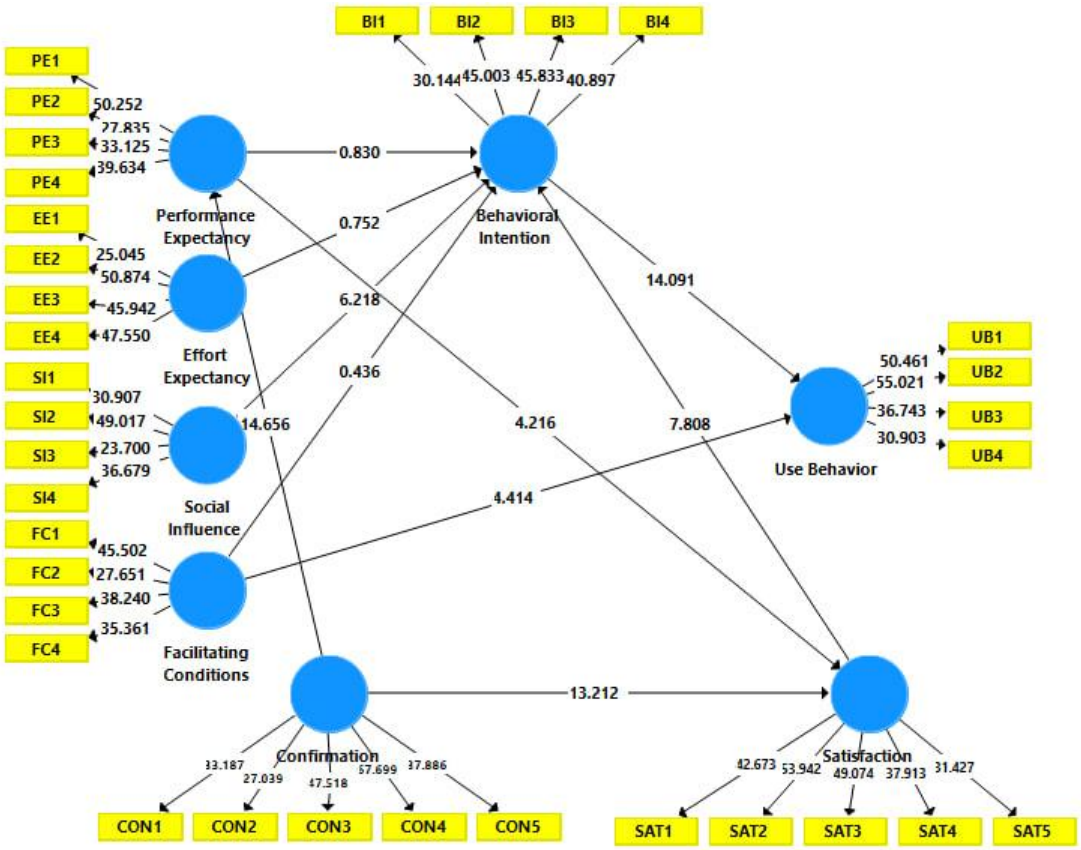

Figure 2: Structural Model and Direct Hypotheses Testing

4. Discussion

The following section discusses the results of hypotheses H1 through H10, examining the factors influencing Cambodian students' behavioral intention and actual use of ChatGPT in higher education. Each hypothesis is analyzed considering UTAUT and expectation confirmation theory, as well as prior empirical studies on AI adoption and educational technology use.

H1 was not supported, as performance expectancy did not have a significant effect on behavioral intention (β = 0.048, t = 0.830, p = 0.407). This result contrasts with evidence from technologically advanced contexts, where performance expectancy is consistently identified as a key predictor of intention to adopt AI-based learning technologies (Miah et al., 2023; Rana et al., 2024; Yakubu et al., 2025). However, the finding aligns with recent studies in developing higher education systems, which suggest that perceived usefulness alone may be insufficient to stimulate adoption intention (Baig & Yadegaridehkordi, 2024; Feng & Haridas, 2025). In the Cambodian context, although students may acknowledge ChatGPT's academic potential, uncertainty surrounding institutional acceptance and ethical use may attenuate the direct influence of performance expectancy on behavioral intention.

H2 was not supported, as effort expectancy did not have a significant effect on behavioral intention (β = 0.039, t = 0.752, p = 0.452). This result diverges from earlier UTAUT-based studies that identified ease of use as a strong predictor of adoption intention (Albayati, 2024; Ma et al., 2025). However, it is consistent with recent generative AI research suggesting that usability has become a basic requirement rather than a motivating factor (Menon & Shilpa, 2023; Valeri et al., 2025). Given Cambodian students' familiarity with mobile and conversational technologies, effort expectancy may no longer differentiate intention levels, indicating that adoption decisions are increasingly driven by post-use value and contextual endorsement rather

than interface simplicity (Lo, 2023; Montenegro-Rueda et al., 2023).

H3 was supported, as social influence had a strong and significant effect on behavioral intention (β = 0.317, t = 6.218, p < 0.001). This finding aligns with prior studies showing that peer, instructor, and institutional endorsement strongly shape students' AI adoption decisions (Owan et al., 2025; Strzelecki et al., 2024). In the Cambodian context, characterized by instructor-centered pedagogy and collectivist norms, students are likely to rely on guidance from lecturers and peers when assessing the appropriateness of ChatGPT use. Similar patterns reported in other Southeast Asian and developing education systems further confirm social influence as a key driver of intention (Maisha & Shetu, 2023; Rana et al., 2024).

H4 was not supported, as facilitating conditions did not significantly influence behavioral intention (β = 0.028, t = 0.436, p = 0.663). This result is consistent with the original UTAUT model, which posits that facilitating conditions primarily affect actual use rather than intention (Venkatesh et al., 2003). Similar findings in recent AI adoption studies indicate that infrastructure and technical support enable usage after intention is formed, rather than motivating intention itself (Alshammari & Alshammari, 2024; Matsiola et al., 2025). In the Cambodian higher education context, students may already anticipate limited institutional support, reducing the relevance of facilitating conditions in shaping their behavioral intention.

H5 was supported, with satisfaction emerging as the strongest predictor of behavioral intention (β = 0.427, t = 7.808, p < 0.001). This result is consistent with expectation-confirmation theory and prior studies identifying satisfaction as a key driver of continuance intention in educational technology use (Chan & Hu, 2023; Ligorio & Rashid, 2025; Niloy et al., 2024). In the context of ChatGPT, students who perceive meaningful academic support, increased efficiency, and enhanced learning outcomes are more likely to sustain their intention to use the tool, reinforcing the view that post-adoption evaluations outweigh pre-adoption beliefs in driving ongoing engagement with generative AI (Baig & Yadegaridehkordi, 2024).

H6 was supported, as confirmation had a strong positive effect on performance expectancy (β = 0.568, t = 14.656, p < 0.001). This finding is consistent with expectation-confirmation theory, which suggests that perceived usefulness is strengthened when actual system performance meets or exceeds users' initial expectations (Polyportis & Pahos, 2025). Similar evidence from AI-supported learning studies indicates that confirmation reshapes students' perceptions of usefulness through direct experience (Chen et al., 2023; Feng & Haridas, 2025). In the Cambodian higher education context, positive confirmation appears to be particularly important in reinforcing the perceived academic value of ChatGPT among students who may initially adopt the technology with uncertainty.

H7 was strongly supported, as confirmation had a significant positive effect on satisfaction (β = 0.622, t = 13.212, p < 0.001). This result is consistent with prior research showing that satisfaction is largely determined by the extent to which users' expectations are met during actual system use (Niloy et al., 2024; Valova et al., 2024). In the context of ChatGPT, confirmation related to output quality, relevance, and reliability appears to enhance student satisfaction, thereby reinforcing continuance behavior and highlighting the importance of managing expectations for effective generative AI use in higher education.

H8 was supported, as performance expectancy had a positive and significant effect on satisfaction (β = 0.215, t = 4.216, p < 0.001). This finding aligns with prior research showing that perceived academic benefits enhance users' evaluative and emotional responses to educational technologies (Ligorio & Rashid, 2025; Mansoor Siddiqui et al., 2025). Although performance expectancy did not directly influence behavioral intention, it remains a key antecedent of satisfaction, indicating that perceived usefulness contributes indirectly to sustained ChatGPT use through satisfaction rather than intention alone.

H9 was supported, as facilitating conditions had a significant positive effect on actual use behavior (β = 0.234, t = 4.414, p < 0.001). This aligns with UTAUT theory and prior studies highlighting the

critical role of infrastructure, connectivity, and institutional support in enabling technology use (Alshammari & Alshammari, 2024; Matsiola et al., 2025). In the Cambodian context, where digital access and institutional readiness vary, facilitating conditions are essential for converting behavioral intention into actual ChatGPT use, underscoring the need for targeted institutional investment and policy support.

H10 was strongly supported, as behavioral intention had a significant positive effect on actual use behavior ($\beta = 0.591$, $t = 14.091$, $p < 0.001$). This finding aligns with core assumptions of both UTAUT and expectation-confirmation theory and is consistent with prior generative AI adoption studies (Duong et al., 2023; Yakubu et al., 2025). The strong effect underscores that intention remains the most direct predictor of ChatGPT use, while also highlighting that intention is largely influenced by satisfaction and confirmation, emphasizing the integration of acceptance and continuance perspectives.

Table 11: Direct Effect Hypotheses Testing

Hypothesis	Coef.	Se	T value	P values	Decision
Performance Expectancy -> Behavioral Intention	0.048	0.058	0.830	0.407	Not Supported
Effort Expectancy -> Behavioral Intention	0.039	0.052	0.752	0.452	Not Supported
Social Influence -> Behavioral Intention	0.317	0.051	6.218	0.000	Supported
Facilitating Conditions -> Behavioral Intention	0.028	0.064	0.436	0.663	Not Supported
Satisfaction -> Behavioral Intention	0.427	0.055	7.808	0.000	Supported
Confirmation -> Performance Expectancy	0.568	0.039	14.656	0.000	Supported
Confirmation -> Satisfaction	0.622	0.047	13.212	0.000	Supported
Performance Expectancy -> Satisfaction	0.215	0.051	4.216	0.000	Supported
Facilitating Conditions -> Use Behavior	0.234	0.053	4.414	0.000	Supported
Behavioral Intention -> Use Behavior	0.591	0.042	14.091	0.000	Supported

Note: Coef. = Coefficient; Se = standard error.

5. Conclusion

This study examined an integrated model of ChatGPT acceptance and continuance among Cambodian undergraduate students, combining UTAUT constructs with expectation confirmation and satisfaction. The findings indicate that social influence and satisfaction are key drivers of students' intention to use ChatGPT, while confirmation shapes both performance expectations and satisfaction. Facilitating conditions and behavioral intention also support actual use, highlighting the importance of both motivational and structural factors in sustaining engagement with generative AI in higher education. The results suggest that universities should leverage social and instructional influence to encourage adoption, ensure that AI tools meet student expectations to foster satisfaction, and provide adequate technological and institutional support to promote continued use.

This research extends UTAUT by integrating post-adoption constructs, offers empirical evidence from a developing higher education context, and highlights context-specific factors such as social influence, confirmation, and satisfaction that shape generative AI engagement. Future studies could adopt longitudinal designs, explore moderating factors such as discipline or digital literacy, conduct cross-country comparisons, and use qualitative methods to capture students' experiences and ethical considerations in AI use.

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