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Determinants of Artificial Intelligence Adoption in Higher Education: Evidence from Cambodian University Students

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Abstract

This study investigates Cambodian university students' attitudes toward artificial intelligence (AI) and the key determinants shaping their behavioural intention to use AI. A cross-sectional survey was administered to 256 students across the multiple higher education institutions in Cambodia. Multiple regression analysis revealed that attitude, perceived ease of use, and facilitating conditions significantly predicted behavioural intention, with attitude emerging as the strongest determinant. In contrast, perceived usefulness, social influence, and ethical and privacy concerns were non-significant, suggesting that students' adoption decisions are driven more by personal evaluations and usability perceptions than by normative pressure or ethical considerations. The findings highlight the need for universities to strengthen AI literacy, develop faculty capacity, and establish ethical guidelines to promote responsible AI use.

Keywords: Artificial intelligence, behavioural intention, Cambodia, higher education, student attitudes

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Introduction

The rapid diffusion of artificial intelligence (AI) in higher education is fundamentally reshaping teaching, learning, and academic support systems worldwide. Recent developments in generative AI tools such as ChatGPT, Gemini, and other large language models have significantly expanded students' access to real-time information processing, academic writing support, and personalized learning assistance. Empirical reports suggest that a substantial proportion of university students globally are already integrating AI-based tools into their academic activities, particularly for content generation, summarization, and problem-solving tasks (Adiguzel et al., 2023; Rahiman & Kodikal, 2024). In the Asia-Pacific region, this adoption trend is accelerating due to increasing digital literacy, institutional digital transformation, and widespread availability of mobile-based AI applications.

Despite these benefits, the integration of AI in higher education has also generated significant concerns. Issues such as academic integrity, overreliance on automated tools, algorithmic bias, and especially data privacy and ethical risks have emerged as critical challenges for universities and policymakers (Cotton et al., 2024; Mortlock & Lucas, 2024). These concerns are particularly relevant in educational environments where regulatory frameworks for AI governance are still evolving.

Empirical evidence suggests that both technological and contextual factors, including usability, perceived value, institutional support, and emerging ethical considerations, shape students' adoption of AI (Budhathoki et al., 2024; Barus et al., 2025). While the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been widely used to explain technology adoption, recent developments in generative AI highlight the need to extend these models to incorporate ethical and privacy concerns, which are closely linked to perceived risk and trust (Ghosh, 2025; Hadan et al., 2026; Li et al., 2025).

Previous studies document multiple determinants of AI adoption in education settings, primarily grounded in TAM and the UTAUT model. Constructs such as perceived usefulness, perceived ease of use, attitude, social influence, and facilitating conditions have consistently been shown to influence users' behavioural intention toward technology adoption (Budhathoki et al., 2024; Barus et al., 2025). However, recent scholarship suggests that these traditional models may not fully capture emerging behavioural dynamics associated with AI technologies, particularly those related to trust, perceived risk, and ethical concerns arising from data-driven systems (Ghosh, 2025; Li et al., 2025).

In developing countries, including those in Southeast Asia, the adoption of AI in higher education is shaped by additional contextual constraints such as digital infrastructure, institutional readiness, and variations in digital literacy among students and faculty (Helmiatin et al., 2024; Vaněček et al., 2025). Cambodia, in particular, represents an under-researched context where higher education is undergoing rapid digital transformation but still faces limitations in technological readiness and policy frameworks governing AI use. As a result, students' perceptions of AI may be influenced not only by perceived usefulness and ease of use but also by concerns related to ethical acceptability and data privacy risks.

However, empirical evidence specifically examining how Cambodian university students evaluate and adopt AI technologies remains extremely limited. More importantly, prior studies have largely overlooked the integration of ethical and privacy concerns into established acceptance models such as TAM and UTAUT, despite increasing recognition of these factors as central determinants of trust in AI systems. This gap restricts our understanding of how cognitive, social, institutional, and ethical factors collectively shape behavioural intention toward AI adoption in higher education. Therefore, this study extends TAM and UTAUT by incorporating ethical and privacy concerns as additional explanatory variables to examine the determinants influencing Cambodian university students' behavioural intention to adopt AI technologies. Specifically, the study addresses the following research questions:

- Do perceived usefulness and perceived ease of use influence students' behavioural intention to adopt AI technologies?
- Do attitude, social influence, and facilitating conditions shape students' intention to use AI?
- To what extent do ethical and privacy concerns affect students' behavioural intention to adopt AI in higher education?

This study contributes to the growing literature on AI adoption in higher education by extending the TAM and UTAUT frameworks through the integration of ethical and privacy concerns within the Cambodian context. The study provides empirical evidence from a developing higher education system where AI governance, institutional readiness, and digital infrastructure remain underexplored. The findings contributed to the theory development and informed institutional and policy strategies for responsible AI integration in Cambodian universities.

Literature Review

AI in Higher Education: Global and Regional Perspectives

Globally, AI is increasingly recognized for its potential to personalize learning, improve academic writing, and enhance knowledge acquisition through adaptive learning systems and generative AI applications (Bouteraa et al., 2024). Such applications have been shown to increase academic performance, engagement, and retention. Progressively, AI in higher education has evolved through multiple technological phases, from rule-based expert systems to machine learning applications, and, more recently, to deep learning-driven AI systems such as large language models (LLMS). This evolution has significantly transformed AI from a supplementary instructional tool into an integrated academic co-pilot within teaching and learning environments.

A global survey conducted by UNESCO (2023) and OECD (2024) revealed that 60-70% of universities worldwide are already using different AI tools in their academic and scholarly activities, such as summarization, assignment drafting, and idea generation. This rapid diffusion reflects the growing normalization of AI as a supplementary academic resource rather than an emerging innovation.

Generative AI tools, including ChatGPT, Claude, Grammarly, QuillBot, Perplexity AI, Copilot, Google Gemini, Khan Academy, and AI-based language learning apps, provide students with flexible, accessible learning support outside the classroom (Habibi et al., 2023; Waluyo & Kusumastuti, 2024). However, research also highlights several barriers to adoption. Strzelecki (2024) found that students in Poland expressed both enthusiasm and scepticism about ChatGPT, citing concerns about reliability and ethical use. In Egypt, students emphasized issues of plagiarism and academic dishonesty (Strzelecki & ElArabawy, 2024). Similar mixed perceptions have been reported in the United States (Lyu & Salam, 2025), where both students and faculty acknowledge AI's potential but insist on clear institutional guidelines.

Institutional and policy responses have also evolved quickly. For instance, UNESCO's (2023) guidelines on generative AI in education stress the importance of ethical governance, openness, and human-centered use of AI in academic institutions. National education authorities have also released policy frameworks that focus on academic integrity, data protection, and responsible AI integration. These policy developments show that more institutions are realizing that using AI in education needs to be balanced with ethical oversight and regulatory preparedness.

Recent multinational studies confirm that usage and attitudes toward generative AI like ChatGPT vary by demographic and contextual factors, underlining the importance of policy environment and AI literacy (Abdaljaleel et al., 2024; Saihi et al., 2024). Comparative evidence across the Asian region illustrates contextual variation in drivers of AI adoption. Studies from Indonesia and Vietnam emphasize institutional encouragement and teacher support as strong predictors of student uptake (Hoi & Mu, 2021; Helmiatin et al., 2024), whereas recent multinational analyses show that cultural, regulatory, and infrastructural differences alter the relative influence of social norms and trust (Budhathoki et al., 2024; Vanecek et al., 2025). For example, a multi-country comparison finds that student attitudes and institutional legitimacy moderate how ethical concerns shape intentions to use generative AI (Budhathoki et al., 2024; Bunduchi et al., 2025).

In Cambodia, emerging research points to both opportunities and challenges in integrating generative AI, including resource limitations, policy gaps, and capacity development needs in teacher education (Sok & Heng, 2024a, 2024b). Attitude studies among Cambodian learners suggest curiosity and openness to AI, alongside concerns about ethics and readiness (Sok et al., 2025). Positioning the Cambodian findings against these regional studies clarifies whether observed effects reflect a national policy/institutional gap or broader regional patterns. Despite this global and regional moment, empirical comprehension of the adoption of AI in higher education remains limited in developing countries.

Perceived Benefits and Challenges of AI

Students often highlight several key benefits of AI in their academic lives. These include improved personalization of learning, enhanced academic efficiency, and opportunities for developing new skills. AI's capacity to provide immediate and adaptive feedback is particularly valued, as it allows students to monitor their progress and adjust their learning strategies (Fauzi et al., 2023; Grassini et al., 2024). Studies have shown that AI use can significantly enhance cognitive and academic productivity by assisting students in different academic activities, enabling students to focus more on critical analysis rather than mechanical tasks. Another advantage lies in AI's ability to expand access to education. For students in resource-limited settings, AI tools can compensate for shortages of teaching staff and learning resources (Bashir & Lapshun, 2025) and reduce disparities in learning opportunities.

Despite these advantages, students also express significant challenges that shape their acceptance and use of AI technologies. One of the significant concerns is data privacy and security, particularly regarding the collection, storage, and potential misuse of personal and academic data by an AI system (Choung et al., 2024; Dahri et al., 2024). Algorithmic bias is another concern, as AI systems trained on biased datasets may perpetuate social inequalities (Anjulo et al., 2025), as many AI models operate as "black-box" systems, making it difficult for users to understand how outputs are generated or decisions are made.

Students are also concerned about academic integrity, with AI tools raising questions about plagiarism, originality, and authorship (Mortlock & Lucas, 2024). LLMs produce incorrect or misleading information, often referred to as hallucinations, which raises concerns about academic credibility and learning accuracy.

Finally, concerns about overreliance on AI highlight potential long-term implications for student learning. Kalnina et al. (2024) indicate that excessive dependence on AI could undermine students' critical thinking and problem-solving abilities. These concerns highlight the importance of fostering AI literacy to ensure that students engage with AI technologies responsibly and effectively.

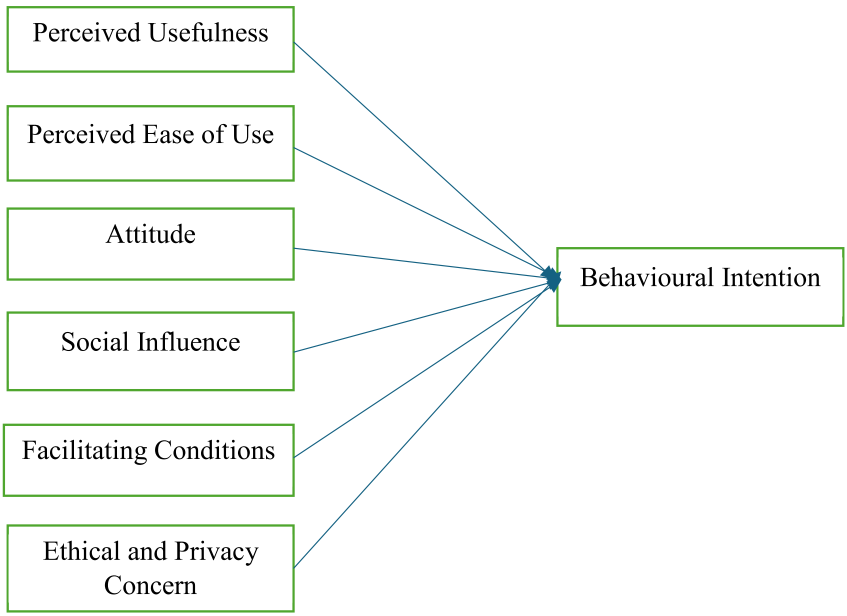
Ethical and Privacy Concern, Trust, and Perceived Risk

Ethical and privacy issues are not only practical concerns but theoretically relevant constructs that interact with TAM/UTAUT processes. Two theoretical pathways are commonly proposed in recent literature. Users often perceive AI technologies as involving risks related to data privacy, algorithmic transparency, surveillance, and misuse of personal information, which can reduce their willingness to adopt such technologies. First, ethical awareness and privacy concern (EPC) function as a perceived risk variable that can directly reduce behavioural intention toward AI adoption (Hadan et al., 2026; Li et al., 2025; Tian et al., 2025). Empirical evidence consistently demonstrates that higher levels of EPC are associated with lower trust, greater uncertainty, and reduced acceptance of AI systems (Song et al., 2024; Mustofa et al., 2025). Although some studies suggest that trust may mediate the relationship between perceived risk and adoption intention, the present study primarily considers EPC as a direct antecedent of behavioural intention.

Research Model

TAM and UTAUT (see Figure 1) provide theoretical frameworks for understanding technology adoption. TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) directly influence attitudes (ATT) and behavioural intention (BI) toward technology (Davis, 1989). Numerous studies confirm that these constructs are strong predictors of AI adoption among students (Chen et al., 2024; Grassini et al., 2024).

Figure 1
Research Model



UTAUT extends TAM by incorporating factors such as social influence (SI) and facilitating conditions (FC; Venkatesh et al., 2003). For example, Mustofa et al. (2025) found that social norms, trust in AI, and ethical concerns significantly shape students' behavioural intention to use AI tools.

Similarly, Bunduchi et al. (2025) emphasize that institutional support and adequate infrastructure are crucial enablers of AI adoption. Together, TAM and UTAUT provide a solid foundation for studying student attitudes toward AI. Yet their application in the Cambodian context remains underexplored, particularly regarding ethical concerns and infrastructural limitations.

Contemporary studies show that while PU and PEOU remain important, constructs such as trust, perceived risk/privacy, and ethical awareness increasingly explain variance in BI toward AI tools (Mustofa et al., 2025; Wiese et al., 2025). For instance, extended TAM/UTAUT studies find that trust mediates the effect of PU and PEOU on intention when users interact with opaque AI systems, whereas perceived privacy risk can suppress adoption despite high perceived usefulness (Li et al., 2025). Cross-disciplinary reviews also emphasize that generative AI's capacity to produce plausible but sometimes incorrect outputs increases users' perceived risk and the need for ethical literacy (Butson & Spronken-Smith, 2024; Ghosh, 2025). These advances suggest that classical TAM/UTAUT variables remain necessary but are insufficient alone for understanding adoption of generative AI in education; theories must integrate socio-technical constructs that capture trust, risk, and ethical awareness.

Despite the rapid proliferation of research on generative AI adoption, several gaps remain. First, most empirical work focuses on high-income or multi-country samples; evidence from Southeast Asian developing contexts, particularly Cambodia, is limited. Second, while TAM and UTAUT remain useful, few studies in the region explicitly test whether ethical and privacy concerns operate as mediators/moderators of the TAM/UTAUT relationships for generative AI in higher education. Third, comparative regional studies suggest institutional support and legitimacy may alter the explanatory power of social influence and perceived usefulness (Bunduchi et al., 2025; Vanecek et al., 2025), but these mechanisms remain under-tested in Cambodia.

This study, therefore, contributes by testing the applicability of an extended TAM/UTAUT model in the Cambodian higher-education context, empirically integrating EPC into the theoretical model, and examining its theoretical role relative to trust/perceived risk, and situating results within regional evidence to clarify context-specific dynamics of AI adoption. Based on the research model above, the following hypotheses are proposed.

Perceived Usefulness and Behavioral Intention to Adopt AI: PU refers to the extent to which students believe that AI technologies can improve their academic performance and learning efficiency (Davis, 1989). TAM proposes that users are more likely to adopt technologies they perceive as beneficial for accomplishing academic tasks. Empirical studies have consistently shown that PU positively predicts students' intention to use AI-powered educational tools and generative AI applications in higher education settings (Chen et al., 2024; Grassini et al., 2024).

H1: Perceived usefulness positively influences behavioral intention to adopt AI technologies.

Perceived Ease of Use and Behavioral Intention to Adopt AI: PEOU describes the degree to which students believe that using AI technologies requires minimal effort (Davis, 1989). Technologies that are simple, intuitive, and accessible are more likely to encourage adoption, particularly in contexts with varying levels of digital literacy. Previous studies have found that ease of use significantly influences students' acceptance of AI applications and digital learning technologies (Dahri et al., 2024; Helmiatin et al., 2024).

H2: Perceived ease of use positively influences behavioral intention to adopt AI technologies.

Attitude and Behavioral Intention to Adopt AI: ATT reflects students' overall positive or negative evaluation of AI technologies. According to TAM, favourable attitudes toward technology increase users' intention to adopt and continuously use digital systems. Prior research demonstrates that positive attitudes toward AI strongly predict BI among university students across different educational contexts (Grassini et al., 2024; Strzelecki, 2024).

H3: Attitude toward AI positively influences behavioral intention to adopt AI technologies.

Social Influence and Behavioral Intention to Adopt AI: SI refers to the extent to which students perceive that important individuals, such as peers, teachers, and institutional leaders, encourage the use of AI technologies (Venkatesh et al., 2003). UTAUT suggests that social norms and peer expectations can shape technology adoption behaviour. Empirical evidence from Asian higher education contexts indicates that teacher support and institutional encouragement positively influence students' intention to adopt digital technologies and AI tools (Helmiatin et al., 2024; Hoi & Mu, 2021).

H4: Social influence positively influences behavioral intention to adopt AI technologies.

Facilitating Condition and Behavioral Intention to Adopt AI: FC refers to students' perceptions of the availability of institutional resources, infrastructure, and technical support necessary for AI adoption. UTAUT proposes that adequate facilitating conditions strengthen users' confidence and ability to use technology effectively. Previous studies have demonstrated that access to digital infrastructure, institutional guidance, and technical assistance significantly influence students' adoption of AI systems in higher education (Bunduchi et al., 2025; Mustofa et al., 2025).

H5: Facilitating conditions positively influence behavioral intention to adopt AI technologies.

Ethical and Privacy Concerns and Behavioral Intention to Adopt AI: EPCs relate to students' perceptions of risks associated with data security, algorithmic bias, transparency, and responsible AI use. Emerging AI adoption literature suggests that concerns regarding privacy and ethics may reduce trust and weaken users' willingness to adopt AI technologies. Empirical studies have reported that greater EPCs negatively influence AI acceptance and BI in educational and technological settings (Song et al., 2024; Li et al., 2025).

H6: Ethical and privacy concerns negatively influence behavioral intention to adopt AI technologies.

Research Methods

The study employed a cross-sectional survey design, which is appropriate for estimating relationships among psychological constructs (Creswell & Clark, 2017). The target population for this study consisted of undergraduate students enrolled in Cambodian higher education institutions during the 2024-2025 academic year. Given the absence of a national student database and the variability across universities, a practical sample size was determined using the common rule of thumb for multiple regression, which recommends a minimum of $N \geq 50 + 8m$ (where m = number of predictors; Field, 2018). With six predictors, the minimum required sample size was 98. The final sample of 256 students exceeded this threshold, ensuring adequate statistical power for regression analysis. This sample size also aligns with recommendations for technology acceptance studies, where samples above 200 yield stable estimates and reliable model performance.

While invitations were distributed broadly across universities, the sampling frame relied on voluntary participation, making it closer to stratified convenience sampling rather than probability sampling. Data was collected through a structured survey questionnaire designed to measure the key constructs of the TAM. The survey was distributed electronically via emails, telegram groups, and in the classrooms facilitated by the teachers. The survey instrument was adapted based on the well-established existing literature. For instance, PU and PEOU were measured using items adapted from Davis (1989), while social influence (SI) and facilitating conditions (FC) were measured using items adapted from Venkatesh et al. (2003). Attitude toward AI (ATT) and behavioural intention (BI) were adapted from Chen et al. (2024). Ethical and privacy concern (EPC) items were adapted from Mustofa et al. (2025) and Abuadas and Albikawi (2026).

The questionnaire consisted of seven constructs measured using multiple items adapted from established scales in previous studies. Perceived usefulness (PU) was measured using four items, PEOU using four items, ATT using four items, BI using four items, SI using four items, FC using four items, and EPC using four items. All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A pilot test was conducted with a small group of university students to ensure clarity, readability, and contextual appropriateness of the questionnaire items before the main data collection process.

Data analysis was conducted using statistical software Jamovi 2.5.5. Descriptive statistics were first computed, which provided an overview of the general attitudes toward AI among students. Before regression analysis, correlation and diagnostic tests were performed. Normality of residuals was verified using P-P plots and Shapiro-Wilk tests. Multicollinearity was examined through Variance Inflation Factors (VIFs). Homoscedasticity and linearity were assessed using residual-versus-fitted plots. Hierarchical regression was used to test the extended model, such as model 1, which included core TAM predictors (PU, PEOU, ATT), and model 2 added UTAUT variables (SI, FC, EPC).

Regarding the ethical consideration, all research procedures were conducted in accordance with established ethical guidelines for studies involving human participants. Participation was entirely voluntary and anonymous, and informed consent was implicitly obtained after respondents were provided with information regarding the study's purpose, confidentiality, voluntary participation, and their right to withdraw at any stage before proceeding with the questionnaire.

Results and Analysis

Socio-Demographic Profile

The socio-demographic profile of the respondents includes age, gender, discipline, and year of study. As presented in Table 1, the majority of respondents were aged between 21 and 30 years (51.6%), whereas female respondents constituted a larger share (58.2%). Regarding academic discipline, most participants were from social science backgrounds (58.6%), dominated by first-year (39.5%) undergraduate students. The profile indicates that the sample largely consists of early-year undergraduate students from social science disciplines, which provides important context for interpreting students' perceptions and behavioural intention toward AI adoption in higher education.

Table 1
Socio-Demographic Profile of Respondents (N = 256)

Variable	Category	n	%
Age	Under 20	112	43.8
	21–30	132	51.6
	31–40	12	4.7
Gender	Male	107	41.8
	Female	149	58.2
Discipline	Social Science	150	58.6
	Arts and Humanities	52	2.3
	Natural Science	8	3.1
	Formal Science	46	18
Year	Year 1	101	39.5
	Year 2	84	32.8
	Year 3	34	13.3
	Year 4	37	14.5

Descriptive Statistics

The descriptive statistics indicate that students generally reported moderate to moderately high perceptions across all constructs. Among the variables, PU (M = 3.473) and ATT toward AI (M = 3.449) demonstrated relatively high mean scores, suggesting generally positive perceptions toward AI technologies. FC showed the lowest mean score (M = 3.190), implying that institutional and technical support for AI use may still be limited.

The standard deviation values indicate a moderate level of variability across all constructs. BI exhibited the highest variability (SD = .976), reflecting greater differences in respondents' intentions to use the technology, whereas PEOU showed the lowest variability (SD = .924), indicating relatively stronger agreement among respondents regarding the ease of technology use.

The Cronbach's alpha values for all constructs exceeded .90, indicating excellent internal consistency reliability. However, values this high may also suggest item redundancy or conceptual overlap. Although this study retained all items to ensure comparability with previous TAM/UTAUT studies, future research may consider revising or shortening item sets through item-total correlations or factor loading analysis.

Table 2

Mean, SD, and Reliability Scores of all Dimensions

Scale	Mean	SD	Cronbach's α
PU	3.473	.952	.917
PEOU	3.402	.924	.912
ATT	3.449	.967	.922
BI	3.407	.976	.938
SI	3.304	.926	.925
FC	3.19	.96	.924
EPC	3.418	.949	.917

Correlation Analysis

Correlation analysis revealed that all key variables were significantly correlated with BI. ATT demonstrated the strongest positive relationship with BI (r = .919), followed by PU (r = .816) and PEOU (r = .802). FC (r = .743), SI (r = .770), and EPC (r = .757) also showed significant positive associations with BI (see Table 3). However, given the relatively high correlations (e.g., ATT–BI and ATT–PU), there is a potential risk of multicollinearity, which was further examined through VIF diagnostics to ensure the robustness of the regression results.

Table 3

Correlation Matrix Among Key Dimensions

	PEOU		PU		ATT		SI		FC		EPC		BI
PEOU	—												
PU	.76	***	—										
ATT	.8	***	.846	***	—								
SI	.711	***	.746	***	.779	***	—						
FC	.699	***	.678	***	.724	***	.861	***	—				
EPC	.71	***	.737	***	.781	***	.777	***	.771	***	—		
BI	.802	***	.816	***	.919	***	.77	***	.743	***	.757	***	—

Note(s). * p < .05, ** p < .01, *** p < .001

Assumption Testing for Regression Analysis

Assumption checks indicated that residuals were approximately normally distributed, as evidenced by the Normal P-P Plot (see Figure 2). Multicollinearity diagnostics showed that VIF values ranged between 2.3 and 5.2, which are below the critical threshold of 10, suggesting no severe multicollinearity issues (see Table 4).

Figure 2

Normal P-P Plot of Regression Standardized Residuals for BI

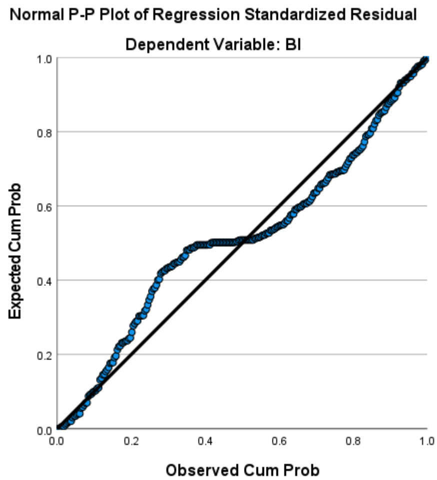


Table 4

Multicollinearity Diagnostics for Regression Model

Predictor	Tolerance	VIF
PU	.248	4.029
PEOU	.312	3.203
ATT	.192	5.205
SI	.196	5.095
FC	.225	4.439
EPC	.287	3.489

Residuals ranged from -1.50 to 1.11 (M = 0, SD = .36), and standardized residuals ranged from -4.12 to 3.05, indicating no extreme outliers and approximate normality. Collinearity diagnostics were examined to assess multicollinearity among predictors (see Table 5). Condition indices ranged from 1.00 to 26.92, which is below the recommended cutoff of 30 (Belsley et al., 1980). Although some variance proportions exceeded .50 in higher dimensions, these did not coincide with condition indices above 30, indicating that multicollinearity was not a major concern.

Table 5

Collinearity Diagnostics for Regression Models Predicting BI

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions						
				(Constant)	PU	PEOU	ATT	SI	FC	EPC
1	1	3.926	1	.0	.0	.0	.0			
	2	.047	9.162	.98	.03	.03	.04			
	3	.017	15.171	.01	.32	.88	.04			
	4	.011	19.32	.01	.64	.09	.91			
2	1	6.861	1	0	0	0	0	0	0	0
	2	.052	11.498	.91	0	0	.01	.01	.03	.01
	3	.032	14.591	.05	.11	.09	.06	.05	.2	.01
	4	.019	19.236	0	.05	.54	.01	0	.07	.43
	5	.017	2.296	.01	.24	.25	.01	.12	0	.5
	6	.01	25.754	.01	.6	.02	.69	.09	.08	.02
	7	.009	26.918	.02	0	.09	.22	.72	.62	.03

Key Determinants of Students' Intentions to Adopt AI Technologies

A hierarchical multiple regression analysis was conducted to examine the predictors of BI to adopt AI technologies among students in Cambodian higher education (see Table 6). Two models were tested. Model 1 included PU, PEOU, and ATT as predictors, and Model 2 extended Model 1 by adding SI, FC, and EPC.

Table 6
Hierarchical Regression of Factors Predicting Students' Behavioural Intention

Predictor	Model 1				Model 2			
	Estimate	SE	*t-value*	*p-value*	Estimate	SE	*t-value*	*p-value*
Intercept	.021	.094	.219	.827	-.026	.095	-.272	.786
PU	.089	.047	1.884	.061	.072	.048	1.499	.135
PEOU	.176	.043	4.074	< .001	.138	.044	3.124	.002
ATT	.718	.05	14.25	< .001	.675	.054	12.569	< .001
SI	-	-	-	-	.003	.055	.053	.958
FC	-	-	-	-	.124	.05	2.487	.014
EPC	-	-	-	-	-.006	.045	-.127	.899
R	.926				.93			
R^2	.858				.865			
F	508.668				265.113			
df	3, 252				6, 249			
p	< .001				< .001			

Model 1 explained a substantial proportion of variance *(R^2=.858)*. Model 2, which included the additional predictors, accounted for slightly more variance *(R^2=.865)*. The change in R^2 between the two models was small but statistically significant *(ΔR^2=.006)*, indicating that adding SI, FC, and EPC improved model fit. The VIF results, however, indicated that multicollinearity remained within acceptable limits, reducing the likelihood of severe model inflation.

In Model 1, ATT was the strongest and most significant predictor of BI (*β=.718, p<.001*), suggesting that students with more positive attitudes were more likely to intend to use AI technologies. PEOU was also a significant predictor (*β=.176, p<.001*), whereas PU showed a positive but marginally nonsignificant relationship with BI (*β=.089, p=.061*).

In Model 2, ATT remained a significant predictor (*β=.675, p<.001*), along with PEOU (*β=.138, p<.001*) and FC (*β=.124, p<.001*). PU, SI, and EPC were not significant predictors when controlling for other variables. The non-significant influence of SI and EPCs suggests that these factors did not significantly affect students' intentions to use AI within the studied context.

Table 7 summarizes the hypothesis testing results, indicating that H2, H3, and H5 were supported, while H1, H4, and H6 were not supported based on the regression analysis.

Table 7
Summary of Hypotheses Testing Results

Hypothesis	Path	Result	Decision
H1	PU → BI	Not significant (*β = .072, p = .135)*	Not supported
H2	PEOU → BI	Significant (*β = .138, p = .002*)	Supported
H3	ATT → BI	Significant (*β = .675, p < .001*)	Supported
H4	SI → BI	Not significant (*β = .003, p = .958*)	Not supported
H5	FC → BI	Significant (*β = .124, p = .014*)	Supported
H6	EPC → BI	Not significant (*β = -.006, p = .899*)	Not supported

Discussion

The findings provide important insights into Cambodian university students' acceptance of AI technologies in higher education. Overall, students reported moderately positive perceptions toward AI, particularly regarding its usability and educational value, which aligns with previous studies on AI adoption in academic settings (Grassini et al., 2024; Waluyo & Kusumastuti, 2024). The analysis revealed that ATT, PEOU, and FC significantly predicted the behavioural intention (BI), whereas PU, SI, and EPC did not show significant direct effects.

ATT emerged as the strongest predictor of BI, reinforcing TAM assumptions that positive evaluations of technology strongly shape adoption behaviour (Davis, 1989). This finding suggests that students' willingness to adopt AI is influenced more by their overall perceptions and comfort with AI than by purely functional considerations. Similar findings have been reported in studies examining AI adoption among university students (Grassini et al., 2024; Strzelecki, 2024).

PEOU also significantly influenced BI, indicating that students are more likely to adopt AI technologies when the systems are accessible and easy to use. In contexts such as Cambodia, where digital literacy and technological access remain uneven, usability becomes a critical factor shaping technology acceptance. This finding is consistent with earlier studies emphasizing the importance of simplicity and accessibility in educational technology adoption (Hoi & Mu, 2021; Dahri et al., 2024; Helmiatin et al., 2024).

FC significantly predicted BI, highlighting the importance of institutional support, infrastructure, and technical resources in facilitating AI adoption. This finding supports UTAUT assumptions that access to organizational and technological support enhances users' willingness to adopt new technologies (Venkatesh et al., 2003). The result also indicates that universities play a central role in shaping students' AI adoption experiences through infrastructure and capacity-building support (Barus et al., 2025; Bunduchi et al., 2025).

In contrast, PU did not significantly predict BI, despite students acknowledging AI's academic benefits. This may indicate that AI use among Cambodian students remains exploratory, where ease of use and personal attitudes are more influential than perceived long-term performance gains. Similarly, SI was not a significant predictor, suggesting that AI adoption is currently driven more by individual perceptions than by peer or institutional influence. This finding contrasts with studies in other Southeast Asian contexts where institutional encouragement and teacher support significantly influenced technology adoption (Hoi & Mu, 2021; Helmiatin et al., 2024).

EPC also showed no significant direct effect on BI. Although students recognized concerns related to responsible AI use, these concerns did not substantially reduce their willingness to adopt AI technologies. This finding aligns with previous studies suggesting that the immediate convenience and perceived benefits of AI may outweigh ethical concerns during the early stage of adoption (Budhathoki et al., 2024; Strzelecki & ElArabawy, 2024). Nevertheless, issues related to privacy, plagiarism, and algorithmic bias remain important considerations as AI technologies become more integrated into higher education practices (Choung et al., 2024; Mortlock & Lucas, 2024).

Thus, the findings suggest that AI adoption in Cambodian higher education is shaped primarily by students' attitudes, usability perceptions, and institutional support rather than by social pressure or ethical concerns. The study extends TAM and UTAUT literature by demonstrating that the influence of technology acceptance factors may vary across developing higher education contexts where AI integration remains emergent.

Conclusion and Implications

This study investigated the determinants influencing Cambodian university students' behavioural intention to adopt AI technologies in higher education by extending the TAM and UTAUT models. The findings revealed that ATT toward AI, PEOU, and FC significantly predicted BI, with ATT emerging as the strongest determinant. The results indicate that students' AI adoption decisions are primarily influenced by positive perceptions toward AI technologies, usability considerations, and institutional support mechanisms.

In contrast, PU, SI, and EPCs did not significantly influence BI when other predictors were controlled. These findings suggest that AI adoption in Cambodian higher education remains at an exploratory stage where students emphasize accessibility and ease of engagement rather than long-term functional value or ethical implications.

The study contributes to the growing literature on AI adoption in higher education by extending TAM and UTAUT through the integration of EPCs within a developing-country context. The findings confirm that traditional technology acceptance variables, particularly ATT and PEOU, remain central determinants of BI toward AI technologies.

The non-significant effects of PU and SI suggest that the explanatory power of TAM and UTAUT constructs may vary depending on contextual conditions and institutional maturity. The findings indicate that in emerging AI environments, students may prioritize usability and personal experience over social norms or long-term performance expectations. The study therefore contributes to theoretical discussions regarding the contextual adaptability of TAMs in developing higher education systems.

The findings indicate that universities should prioritize the development of user-friendly and accessible AI learning environments. Since PEOU significantly influenced BI, institutions should provide practical AI training programs, digital literacy workshops, and orientation sessions to improve students' confidence and competence in using AI technologies.

The significance of FCs further highlights the importance of institutional investment in technological infrastructure, internet accessibility, AI learning platforms, and technical support services. Universities should also strengthen faculty capacity through professional development programs that encourage responsible and pedagogically meaningful integration of AI into teaching and learning activities.

Additionally, the findings suggest that positive student attitudes toward AI can be strengthened through awareness campaigns, classroom demonstrations, and responsible exposure to AI-supported academic practices.

The findings emphasize the urgent need for clearer institutional and national policy frameworks governing AI use in higher education. Although EPCs did not significantly reduce BI, students still expressed moderate awareness regarding responsible AI use, data privacy, and academic integrity.

Cambodian universities and higher education authorities should therefore establish formal AI governance guidelines addressing plagiarism, transparency, data protection, ethical AI usage, and responsible academic practices. National policies promoting AI literacy and equitable digital access should also be developed to support safe and inclusive AI integration across Cambodian universities.

In addition, ministries and educational regulators may consider developing standardized frameworks for AI implementation, faculty training, and digital ethics education to ensure sustainable and responsible AI adoption within the higher education sector.

Limitations and Future Research

This study has several limitations that need to be acknowledged. Although students were drawn from multiple universities, the sample may overrepresent urban institutions with better digital connectivity and greater exposure to AI technologies. Students from rural universities may have different levels of access, awareness, and attitudes toward AI. In addition, the reliance on self-reported data introduces the possibility of social desirability bias or inaccurate self-assessment, which may affect the precision of constructs such as attitude, usefulness, or ethical concerns.

Future studies could build on this work by employing longitudinal designs to capture changes in perceptions as AI becomes more embedded in Cambodian higher education. Qualitative research could also explore the critical aspects of why usefulness and SI exert weaker effects, providing deeper insights into cultural and institutional dynamics. Additionally, future research should examine the moderating variables that may shape AI adoption behaviour. Gender differences, disciplinary backgrounds, and levels of digital literacy may influence how students PU, PEOU, and ethical risks associated with AI. Additionally, future studies could use multi-group analysis or structural equation modelling to compare different student subpopulations and identify divergent adoption pathways.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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