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AI Tool Adoption and Its Impact on Perceived Learning Outcomes Among University Students in Cambodia

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ABSTRACT

The rapid advancement of artificial intelligence (AI) technologies has transformed higher education by enabling students to use intelligent tools that support academic learning. In Cambodia, university students increasingly use AI tools such as ChatGPT, Gemini, and Copilot; however, empirical evidence regarding their impact on learning remains limited. This study examines the level of AI tool adoption and its relationship with perceived learning outcomes. A quantitative cross-sectional survey was conducted with 301 university students across Cambodia. Descriptive statistics, reliability analysis, Pearson correlation, and simple linear regression were employed for data analysis. The results indicate a moderate level of AI tool adoption ($M = 3.46$, $SD = 0.90$) and moderately positive perceived learning outcomes ($M = 3.50$, $SD = 0.85$). A strong positive relationship was found between AI tool adoption and perceived learning outcomes ($r = 0.771$, $p < 0.001$). Regression analysis shows that AI tool adoption significantly predicts perceived learning outcomes ($R^2 = 0.595$). These findings suggest that AI tools can serve as effective learning support tools when used appropriately. The study provides empirical evidence for guiding AI integration in Cambodian higher education.

Keywords: Artificial Intelligence, Higher Education, Learning Outcomes, Technology Adoption, University Students, Cambodia

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1. Introduction

Background of the study

Artificial Intelligence (AI) has rapidly evolved from a specialized computational concept into a mainstream technology shaping contemporary society. In recent years, generative AI systems such as large language models, automated writing assistants, and intelligent tutoring platforms have become widely accessible to university students (Holmes et al., 2019; Zawacki-Richter et al., 2019). These tools allow users to generate academic content, summarize readings, translate materials, and receive instant feedback (Kasneci et al., 2023; Rasiah et al., 2023). Scholars argue that AI technologies are transforming higher education by reshaping learning processes, assessment practices, and academic engagement (Holmes et al., 2019; Zawacki-Richter et al., 2019).

Although AI tools have become increasingly accessible, empirical investigations examining how students integrate these tools into their academic routines remain limited, particularly in developing country contexts. While international studies highlight both opportunities and risks associated with AI usage in higher education (Zawacki-Richter et al., 2019; Dwivedi et al., 2023; Cotton et al., 2023), contextualized research is necessary to understand how these technologies influence students' learning experiences within specific national educational systems.

The adoption of new technologies in education is not a novel phenomenon. Theoretical frameworks such as the Technology Acceptance Model (TAM) suggest that perceived usefulness and perceived ease of use significantly influence individuals' willingness to adopt digital systems (Davis, 1989). Similarly, Ajzen's (1991) Theory of Planned Behavior highlights the role of attitudes and perceived behavioral control in shaping user behavior. These theoretical perspectives provide a foundation for understanding why university students choose to integrate AI tools into their academic activities. However, while technology adoption theories explain why students may adopt AI tools, they do not fully address whether such adoption translates into meaningful academic benefits. Therefore, integrating technology acceptance perspectives with learning outcome frameworks provides a more comprehensive analytical approach for examining AI usage in higher education.

Recent global research indicates that AI applications in higher education can enhance learning efficiency, increase access to information, and support personalized instruction

(Chen et al., 2020; Luckin et al., 2016). AI-powered systems have been found to assist students in improving writing skills, understanding complex concepts, and managing study time more effectively (Kasneci et al., 2023). Furthermore, digital learning environments supported by intelligent systems may foster greater learner autonomy and engagement (Bond et al., 2020).

Despite these potential benefits, scholars also raise concerns regarding academic integrity, overreliance on automated systems, and potential reduction in critical thinking development (Cotton et al., 2023; Dwivedi et al., 2023). The emergence of generative AI tools such as ChatGPT has triggered significant debate in universities worldwide regarding ethical usage, policy adaptation, and instructional redesign (Baidoo-Anu & Owusu Ansah, 2023). These discussions highlight the importance of empirical research examining how students actually use AI tools and how such usage influences their perceived learning outcomes.

Within Southeast Asia, digital transformation in higher education is accelerating, particularly following the expansion of online and hybrid learning environments during and after the COVID-19 pandemic (Crawford et al., 2020; Rasiah et al., 2022). Cambodian universities have increasingly adopted digital platforms to support remote instruction and blended learning models (Heng & Doeur, 2022). However, empirical research examining AI tool adoption among Cambodian university students remains limited. Most existing literature focuses on developed educational systems, leaving a contextual gap in developing countries (Zawacki-Richter et al., 2019).

Understanding AI tool adoption in Cambodia is essential for several reasons. First, higher education institutions require evidence-based insights to formulate policies regarding AI integration. Second, educators must understand whether AI tools enhance or undermine student learning. Third, policymakers need empirical data to guide digital education strategies. Without local research evidence, institutional decisions risk being based on assumptions rather than systematic investigation.

Problem statement

Although AI tools are increasingly used by university students in Cambodia (Sol et al., 2025), their impact on learning outcomes remains unclear. While international studies suggest that AI technologies can enhance learning efficiency and engagement (Chen et al., 2020; Holmes et al., 2019), concerns remain regarding ethical use and academic dependency (Cotton et al., 2023; Dwivedi et al., 2023).

In the Cambodian context, limited research has systematically examined both the level of AI tool adoption and its relationship with perceived learning outcomes, although there have been studies examining AI use among Cambodian students (Hoeurng et al., 2024; Sol et al., 2025; Sok et al., 2025; Tao, 2026). This lack of localized empirical evidence restricts the ability of higher education institutions to develop evidence-based policies and strategies for responsible AI integration.

Research objectives

This study aims to:

1. Examine the level of AI tool adoption among university students in Cambodia.
2. Assess students' perceived learning outcomes associated with the use of AI tools in academic activities.
3. Analyze the relationship between AI tool adoption and perceived learning outcomes among university students.
4. Evaluate the predictive effect of AI tool adoption on perceived learning outcomes.

Research questions

This study is guided by four research questions:

RQ1: What is the level of AI tool adoption among university students in Cambodia?
RQ2: What is the level of perceived learning outcomes associated with the use of AI tools in academic learning?
RQ3: Is there a significant relationship between AI tool adoption and perceived learning outcomes?
RQ4: Does AI tool adoption significantly predict perceived learning outcomes among university students?

Significance of the Study

Academic Contribution

This study contributes to the literature by providing empirical evidence on AI tool adoption and perceived learning outcomes within the Cambodian higher education context. The findings offer practical insights for educators, institutions, and policymakers in developing strategies for responsible AI integration in teaching and learning.

Institutional Implications

The findings of this study provide practical insights for university administrators and educators regarding the role of AI tools in academic settings. Understanding whether AI tool adoption positively influences perceived learning outcomes enables institutions to design informed strategies for responsible AI integration, curriculum adaptation, and student digital literacy development. The results may assist universities in formulating evidence-based guidelines that balance innovation with academic integrity, ensuring that AI technologies enhance rather than undermine student learning experiences.

Policy Implications

At the policy level, this research offers valuable empirical data to support decision-making related to digital transformation in Cambodian higher education. As AI technologies become increasingly embedded in educational environments, policymakers require localized evidence to develop regulatory frameworks and governance mechanisms that promote ethical and effective AI usage. Furthermore, the study provides baseline empirical data that may guide future longitudinal and experimental research examining objective academic performance indicators, thereby strengthening the foundation for evidence-based educational reform in Cambodia.

2. Literature Review

Definition of Key Terms

Artificial Intelligence in Education

Artificial Intelligence (AI) refers to computational systems capable of performing tasks that normally require human intelligence, including reasoning, pattern recognition, learning, and language processing (Russell & Norvig, 2021). In educational contexts, AI encompasses a wide range of applications, including intelligent tutoring systems, adaptive learning platforms, automated grading systems, predictive analytics, and more recently, generative AI tools such as large language models (Holmes et al., 2019; Luckin et al., 2016).

AI in higher education is often categorized into administrative AI, instructional AI, and learner-support AI (Chen et al., 2020). Administrative AI includes automated scheduling and student support systems. Instructional AI includes intelligent tutoring systems that personalize learning experiences. Learner-support AI includes writing assistants, language models, and chat-based systems that provide instant academic feedback (Zawacki-Richter et al., 2019).

The emergence of generative AI systems such as ChatGPT has significantly expanded AI's role in education. These tools are capable of producing contextually relevant text, summarizing complex materials, generating explanations, and assisting with research tasks (Dwivedi et al., 2023; Kasneci et al., 2023). Such capabilities have transformed how students access and process academic information.

AI Tool Adoption

Technology adoption refers to the process by which individuals accept and integrate new technological systems into their daily activities (Rogers, 2003). Rogers' (2003) Diffusion of Innovations theory emphasizes that adoption depends on perceived relative advantage, compatibility, complexity, trial ability, and observability. In educational environments, student adoption of digital tools is often influenced by perceived academic benefits and technological readiness.

The Technology Acceptance Model (TAM), developed by Davis (1989), proposes that perceived usefulness and perceived ease of use are primary determinants of technology adoption. Numerous studies have validated TAM within educational contexts (King & He, 2006; Teo, 2011). The Unified Theory of Acceptance and Use of Technology (UTAUT) extends TAM by incorporating social influence and facilitating conditions (Venkatesh et al., 2003; Venkatesh et al., 2012).

In higher education, student adoption of e-learning platforms and digital tools has been shown to be influenced by performance expectancy and technological self-efficacy (Al-Emran et al., 2018; Nikolopoulou et al., 2020). These theoretical models provide an explanatory framework for understanding AI tool adoption among university students.

Perceived Learning Outcomes

Learning outcomes refer to measurable knowledge, skills, competencies, and attitudes acquired through educational experiences (Biggs & Tang, 2011). Perceived learning outcomes, however, reflect students' subjective evaluation of their learning progress and academic development (Eom & Ashill, 2016).

In digital education research, perceived learning outcomes commonly include improved understanding of course material, increased academic confidence, enhanced engagement, and better time management (Kuo et al., 2014; Sun et al., 2008). Perception-based measures are widely accepted in educational research because they capture cognitive and affective dimensions of learning experiences (Richardson et al., 2017).

Although objective academic performance indicators such as GPA provide measurable outcomes, perceived learning outcomes offer valuable insight into students' evaluation of educational tools and technologies (Richardson et al., 2017).

Review of Existing Literature

AI in Higher Education

Research on AI in higher education has expanded significantly over the past decade. Luckin et al. (2016) argue that AI can support personalized instruction by adapting learning content based on individual performance patterns. Similarly, Holmes et al. (2019) emphasize that AI technologies enhance student engagement through intelligent feedback systems and adaptive learning environments.

Chen et al. (2020) highlight that AI systems improve efficiency in higher education by automating repetitive tasks and providing real-time academic assistance. Additionally, Hwang et al. (2020) suggest that AI-supported learning environments can foster deeper conceptual understanding when integrated appropriately.

However, scholars also identify challenges associated with AI implementation. Cotton et al. (2023) and Baidoo-Anu and Owusu Ansah (2023) emphasize concerns regarding academic integrity and ethical usage of generative AI systems. Dwivedi et al. (2023) argue that while generative AI presents significant educational opportunities, it also requires governance frameworks to mitigate misuse.

Zawacki-Richter et al. (2019) conducted a systematic review and found that most AI research in higher education focuses on predictive analytics rather than direct student learning outcomes. This gap underscores the need for empirical studies examining how AI adoption influences perceived academic improvement.

Technology Adoption in Educational Contexts

Technology adoption theories remain central to understanding digital engagement in education. Davis (1989) demonstrated that perceived usefulness significantly predicts user acceptance of information systems. Subsequent meta-analyses confirm the robustness of TAM in educational settings (King & He, 2006).

Venkatesh et al. (2003) integrated multiple models to propose UTAUT, identifying performance expectancy as the strongest predictor of technology usage. In educational contexts, performance expectancy corresponds to students' belief that AI tools enhance academic performance.

Studies examining digital learning adoption reveal that students are more likely to adopt technology when it improves efficiency and reduces cognitive effort (Al-Emran et al., 2018; Teo, 2011). Furthermore, digital literacy and prior technological experience significantly influence adoption rates (Nikolopoulou et al., 2020).

In developing countries, contextual factors such as infrastructure and institutional support play critical roles in technology adoption (Rasiah et al., 2022; Tarhini et al., 2017). Therefore, examining AI adoption within Cambodia requires attention to local educational environments.

AI and Learning Outcomes

The relationship between digital tools and learning outcomes has been widely studied. Richardson et al. (2017) found that student engagement strongly predicts academic achievement in digital environments. Sun et al. (2008) identified learner satisfaction as a key determinant of perceived learning effectiveness.
Recent studies suggest that generative AI tools may enhance productivity and comprehension by providing immediate academic assistance (Kasneci et al., 2023). Hwang et al. (2020) argue that AI-supported systems can facilitate higher-order thinking when integrated into instructional design.

However, excessive reliance on AI-generated content may reduce independent problem-solving skills (Dwivedi et al., 2023). Therefore, empirical research is necessary to determine whether AI adoption positively correlates with perceived learning outcomes.

In Southeast Asia, digital transformation in higher education accelerated during the COVID-19 pandemic (Bond et al., 2020; Crawford et al., 2020). Cambodian universities adopted online platforms to sustain academic continuity (Heng & Doeur, 2022). Despite these developments, limited research examines how AI tools specifically influence Cambodian students' learning experiences.

Theoretical Foundation

This study integrates the Technology Acceptance Model (Davis, 1989), Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), and Diffusion of Innovations theory (Rogers, 2003) to explain AI tool adoption behavior. These frameworks collectively suggest that perceived usefulness, social influence, and perceived benefits significantly influence technology usage.

In addition, perceived learning outcomes are grounded in digital learning theory, which emphasizes learner engagement, cognitive processing, and self-regulated learning (Richardson et al., 2017). By combining adoption theory and learning outcome perspectives, this study establishes a multidimensional framework for analyzing AI tool usage in higher education.

Conceptual Framework

Based on technology adoption theory (Davis, 1989; Venkatesh et al., 2003) and educational outcome literature (Richardson et al., 2017), this study proposes that AI tool adoption positively influences perceived learning outcomes among university students.
The conceptual framework is structured as follows:
AI tool adoption positively influences perceived learning outcomes.

This framework integrates innovation diffusion theory (Rogers, 2003), TAM, and digital learning outcome research to provide a comprehensive foundation for empirical analysis.

Figure 1. Conceptual Framework of the Study

Research Hypotheses

Based on technology adoption theory and digital learning literature, the following hypotheses are proposed:

H1: AI tool adoption is positively associated with perceived learning outcomes among university students.
H2: AI tool adoption significantly predicts perceived learning outcomes.

3. Methods

Research design

This study adopted a quantitative research design using a cross-sectional survey approach to examine the relationship between AI tool adoption and perceived learning outcomes among university students in Cambodia. Quantitative research is appropriate for testing theoretical relationships between measurable variables and examining predictive associations (Creswell & Creswell, 2018; Teo, 2011).

A cross-sectional design allows data collection at a single point in time, enabling efficient analysis of relationships between variables without requiring longitudinal follow-up

(Bryman, 2016; Fowler, 2014). This approach is widely applied in educational technology and technology adoption studies due to its efficiency and suitability for perception-based research.

Survey methodology has been extensively used in studies based on the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). These models rely on perception-based measurement scales that are commonly analyzed using correlation and regression techniques, making a structured questionnaire appropriate for this study.

Table 1. Measurement of Constructs

Construct	Number of Items	Measurement Scale	Sources
AI Tool Adoption	6	5-point Likert scale (1 = Never, 2 = Rarely, 3 = Occasionally, 4 = Frequently, 5 = Very Frequently)	Davis (1989); Venkatesh et al. (2003)
Perceived Learning Outcomes	6	5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree)	Sun et al. (2008); Eom and Ashill (2016)

Research site

The study was conducted within the Cambodian higher education context. Cambodia's university system has undergone significant digital transformation in recent years, particularly following the widespread adoption of online and blended learning platforms during the COVID-19 pandemic (Heng & Doeur, 2022; Rasiah et al., 2022). This transformation has increased students' exposure to digital tools and AI-supported technologies.

Respondents were recruited from multiple universities across Cambodia through online student communication platforms, including Telegram academic groups and institutional networks. Online distribution was selected due to its accessibility, efficiency, and compatibility with digital-native student populations (Wright, 2005). Since AI tool usage primarily occurs in digital environments, collecting data through online platforms is consistent with the technological context of the research topic.

Target population

The target population consisted of students currently enrolled in Bachelor's, Master's, and PhD programs at accredited universities in Cambodia. University students were selected as the unit of analysis because they represent the primary users of AI tools for academic purposes. Students engage with AI tools in coursework, assignments, research activities, and independent study, making them the most relevant population for this investigation.

The study focuses on perceived learning outcomes rather than objective academic performance. Perception-based research is widely accepted in educational technology studies because students' subjective experiences provide valuable insight into technology effectiveness (Richardson et al., 2017).

Sampling technique

A non-probability convenience sampling method was employed due to accessibility constraints and the exploratory nature of the study. Convenience sampling is commonly used in educational research when random sampling is not feasible (Etikan et al., 2016). Although probability sampling enhances generalizability, convenience sampling remains appropriate for perception-based survey studies, particularly when investigating emerging technological phenomena.

The survey link was distributed through student groups and academic networks. Participation was voluntary, and no incentives were provided. While convenience sampling may limit external generalizability, the approach is widely accepted in technology adoption research (Tarhini et al., 2017).

Sample size

A target sample size of approximately 300 respondents was established prior to data collection. In regression analysis, sample size plays an important role in ensuring adequate statistical power (Hair et al., 2019). Tabachnick and Fidell (2013) suggest that the minimum sample size can be estimated using the formula $N \geq 50 + 8m$, where 'm' represents the number of independent variables.

Given that the model in this study includes one predictor (AI tool adoption), the required minimum sample size is 58. The final sample of 301 respondents exceeds this requirement and is therefore considered sufficient for the analysis.

Respondent profile

Demographic variables collected included gender, level of study (Bachelor's, Master's, PhD), field of study, and type of university (public or private). Descriptive statistical analysis was conducted to summarize the characteristics of respondents. Understanding respondent profiles allows the examination of potential demographic differences in AI adoption behavior.

Research instrument and measurement of constructs

The research instrument consisted of a structured questionnaire divided into multiple sections: demographic information, AI tool usage screening, AI adoption items, and perceived learning outcome items.

AI tool adoption

AI tool adoption was measured using multiple Likert-scale items assessing frequency of use, reliance on AI tools for academic tasks, perceived importance of AI in learning, and comfort in using AI systems. These items were adapted conceptually from technology acceptance literature (Davis, 1989; Venkatesh et al., 2003). Although the present study does not directly measure TAM constructs such as perceived usefulness, the adoption items capture behavioral engagement consistent with technology acceptance theory.

Perceived learning outcomes

Perceived learning outcomes were measured using Likert-scale items assessing improved understanding of course materials, increased study efficiency, enhanced academic confidence, and overall positive learning experience. These measures align with prior online learning and digital education studies (Eom & Ashill, 2016; Sun et al., 2008).

All items were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Likert scales are widely utilized in educational research because they provide reliable ordinal measurement while allowing parametric statistical analysis under appropriate assumptions (Joshi et al., 2015).

AI tool adoption was measured using six items, and perceived learning outcomes were measured using six items. Composite scores were computed by averaging item responses. Higher mean scores indicate higher levels of AI tool adoption and perceived learning outcomes.

Data collection procedure

Data were collected through an online survey platform. Online surveys are advantageous in higher education research because they facilitate rapid data collection, reduce administrative costs, and increase accessibility (Wright, 2005). Respondents accessed the survey link through digital communication channels.

Prior to answering survey questions, participants were required to provide informed consent. The survey did not collect names, student IDs, email addresses, or other identifying information. Data collection continued until approximately 301 valid responses were obtained. Responses were screened to remove incomplete or invalid submissions prior to analysis.

A screening question was included to identify respondents who had prior experience using AI tools for academic purposes. Only respondents who indicated prior use of AI tools were included in the main statistical analysis examining the relationship between AI tool adoption and perceived learning outcomes.

Data analysis

Data were analyzed using the Statistical Package for the Social Sciences (SPSS). Data analysis followed a systematic sequence. First, data cleaning was performed to identify missing values, outliers, and inconsistent responses (Field, 2018). Descriptive statistics were calculated to determine mean scores and standard deviations for AI adoption and perceived learning outcomes.

Second, internal consistency reliability was assessed using Cronbach's alpha (Cronbach, 1951). An alpha value of 0.70 or above was considered acceptable, indicating adequate internal consistency (Nunnally & Bernstein, 1994). Third, Pearson correlation analysis was conducted to examine the strength and direction of the relationship between AI tool adoption and perceived learning outcomes. Correlation coefficients range from −1 to +1, with values closer to +1 indicating stronger positive relationships (Hair et al., 2019). Prior to regression analysis, statistical assumptions including normality, linearity, homoscedasticity, and multicollinearity were examined (Hair et al., 2019).

Finally, simple linear regression analysis was performed to determine whether AI tool adoption significantly predicts perceived learning outcomes among university students. Regression analysis is appropriate for testing predictive relationships between independent and dependent variables (Tabachnick & Fidell, 2013). In this model, AI tool adoption was treated as the independent variable, while perceived learning outcomes served as the dependent variable. Statistical significance was evaluated at the 0.05 level.

Ethical considerations

Ethical standards were observed throughout the research process. Participants were informed about the purpose of the study and provided voluntary consent before proceeding with the survey. The questionnaire was anonymous, and no personally identifiable information was collected. Participation was voluntary, and respondents could discontinue at any time prior to submission.

These procedures align with established ethical guidelines for social science research involving human participants (Resnik, 2018). Data were used solely for academic analysis and publication purposes.

4. Results and Discussions

Respondent demographic profile

The demographic characteristics of the respondents are summarized in Table 2. A total of 301 valid responses were included in the analysis.

In terms of gender distribution, the majority of respondents were male (70.4%), followed by female (28.2%), while 1.3% identified as other. Regarding age, most respondents were between 18–20 years old (37.9%), followed by 21–23 years old (33.6%), indicating that the sample primarily consists of young undergraduate students.

With respect to the year of study, Year 2 bachelor's students accounted for the largest proportion (23.3%), followed by Master's degree students (20.9%), Year 1 (19.6%), and Year 3 (19.6%), while Year 4 students represented 14.3% of the sample. Only a small proportion of respondents were enrolled in doctoral programs (0.7%) or other categories (1.7%).

Regarding academic discipline, the majority of respondents were from Information Technology or Computer Science programs (55.1%), followed by Other fields (21.6%) and Business or Management (13.0%). Smaller proportions were from Education (5.0%), Engineering (2.3%), Social Sciences (2.0%), and Health Sciences (1.0%).

In terms of university type, 54.5% of the respondents were enrolled in private universities, while 45.5% were from public universities. Regarding internet access quality, most students reported having good internet access (45.5%), followed by moderate internet quality (30.9%), while smaller proportions reported very good (12.0%), poor (7.6%), and very poor (4.0%) internet connectivity.

These demographic results indicate that the survey captured responses from students across diverse academic levels, fields of study, and institutional contexts.

Table 2. Demographic Profile of the Respondents (N = 301)

Variable	Category	Frequency	Percentage (%)
Gender	Male	212	70.4
	Female	85	28.2
	Other	4	1.3
Age (year)	18–20	114	37.9
	21–23	101	33.6
	24–26	32	10.6
	27 and above	54	17.9
Year of Study	Doctoral (PhD)	2	0.7
	Master's Degree	63	20.9
	Year 1 (Bachelor)	59	19.6
	Year 2 (Bachelor)	70	23.3
	Year 3 (Bachelor)	59	19.6
	Year 4 (Bachelor)	43	14.3
	Other	5	1.7

(To be continued)

Table 2. Demographic Profile of the Respondents (N = 301) (continued)

Variable	Category	Frequency	Percentage (%)
Field of Study	Information Technology / Computer Science	166	55.1
	Business / Management	39	13.0
	Education	15	5.0
	Engineering	7	2.3
	Social Sciences	6	2.0
	Health Sciences	3	1.0
	Other	65	21.6
University Type	Private University	164	54.5
	Public University	137	45.5
Internet Quality	Very Good	36	12.0
	Good	137	45.5
	Moderate	93	30.9
	Poor	23	7.6
	Very Poor	12	4.0

Descriptive statistics

Descriptive statistics were calculated to examine the central tendency and variability of the study variables, including AI tool adoption and perceived learning outcomes. The analysis included 301 valid responses.

As shown in Table 3, the composite mean score for AI tool adoption is 3.46 (SD = 0.90), indicating that AI tools are used between "occasionally" and "frequently" among university students in Cambodia. The composite mean score for perceived learning outcomes is 3.50 (SD = 0.85), indicating responses between "neutral" and "agree," suggesting that students generally perceive AI tools as having a positive influence on their learning experiences.

The reliability analysis indicates good internal consistency for both constructs, with Cronbach's alpha values of 0.842 for AI tool adoption and 0.851 for perceived learning outcomes. These values exceed the recommended threshold of 0.70, indicating that the measurement scales are reliable for further analysis.

Table 3. Descriptive Statistics and Reliability of Study Variables

Variable	N	Mean	SD	Cronbach's Alpha
AI Adoption	301	3.46	0.90	0.842
Perceived Learning Outcomes	301	3.50	0.85	0.851

Correlation and Regression Analysis

Pearson correlation analysis was conducted to examine the relationship between AI tool adoption and perceived learning outcomes among university students. The results, as presented in Table 4, indicate a strong positive correlation between AI tool adoption and perceived learning outcomes ($r = 0.771$, $p < 0.001$). This suggests that students who demonstrate higher levels of AI tool adoption tend to report more positive perceived learning outcomes. These findings provide empirical support for Hypothesis 1, which proposed a positive relationship between AI tool adoption and perceived learning outcomes.

A linear regression analysis was conducted to examine the predictive effect of AI tool adoption on perceived learning outcomes. The results indicate that AI tool adoption has a positive and statistically significant effect on perceived learning outcomes ($B = 0.730$, $t = 20.947$, $p < 0.001$). The model explains 59.5% of the variance in perceived learning outcomes ($R^2 = 0.595$), indicating strong explanatory power.

The 95% confidence interval for the coefficient ranges from 0.661 to 0.798, indicating that the true population parameter is likely to fall within this range. Because the interval does not include zero, the coefficient is statistically significant at the 0.05 level, providing evidence of a positive relationship between the variables.

Table 4. Results of Correlation and Regression Analysis

Variable	B	Std. Error	Beta	t	p
Constant	0.983	0.124	-	7.900	.000
AI Tool Adoption	0.730	0.035	0.771	20.947	.000

Model Summary

R	R^2	Adjusted R^2
0.771	0.595	0.593

ANOVA

F(df)	p-value
F(1, 299) = 438.784	< 0.001

Correlation

Variables	r	p-value
AI Tool Adoption – PLO	0.771	< 0.001

Discussion

The findings of this study provide empirical evidence regarding the relationship between AI tool adoption and perceived learning outcomes among university students in Cambodia. The results indicate that students demonstrate a moderate level of AI tool adoption, with an overall mean score above the midpoint of the five-point Likert scale. This suggests that AI tools are increasingly becoming part of students' academic activities, supporting tasks such as information retrieval, idea generation, and learning assistance.

The findings also reveal that students report positive perceptions of learning outcomes associated with AI tool usage. The composite mean score for perceived learning outcomes indicates that students generally believe AI tools contribute positively to their academic learning experience. This suggests that AI technologies may help students better understand course materials, improve learning efficiency, and support independent learning.

More importantly, the correlation analysis shows a strong positive relationship between AI tool adoption and perceived learning outcomes ($r = 0.771$, $p < 0.001$). This indicates that students who use AI tools more frequently tend to report higher perceived improvements in their learning outcomes. The regression analysis further confirms that AI tool adoption significantly predicts perceived learning outcomes, explaining a substantial proportion of the variance in students' perceived learning benefits.

These findings are consistent with previous research on the role of artificial intelligence in education. For example, Holmes et al. (2019) highlighted that AI technologies can enhance personalized learning experiences and support student engagement in digital learning environments. Similarly, Zawacki-Richter et al. (2019) found that AI-based educational tools can facilitate adaptive learning and improve students' access to academic resources. More recent studies focusing on generative AI tools have also reported similar outcomes. For instance, Kasneci et al. (2023) noted that AI tools such as ChatGPT can support students' understanding of complex academic concepts and assist in learning-related tasks when used responsibly.

These findings are also aligned with emerging studies in the Cambodian context. For example, Sol et al. (2025) reported that Cambodian university students increasingly use AI tools to support academic tasks, particularly in language learning and assignment preparation. Similarly, Heng and Doeun (2022) observed that digital transformation initiatives in Cambodian higher education have accelerated the adoption of technology-enhanced learning practices. These local findings reinforce the present study's results, highlighting the growing role of AI technologies in shaping learning experiences within Cambodian higher education.

The results of this study therefore support the broader literature suggesting that AI technologies can play a supportive role in higher education learning environments (Holmes et al., 2019; Zawacki-Richter et al., 2019; Kasneci et al., 2023) However, it is important to recognize that the positive impact of AI tools depends on how they are used by students. Responsible and ethical use of AI technologies remains essential to ensure that these tools enhance learning rather than replace students' own critical thinking and academic effort.

Overall, the findings suggest that AI tools have the potential to support and enhance students' learning experiences, particularly when integrated appropriately within digital learning environments in higher education institutions.

5. Conclusion

This study examined the adoption of AI tools among university students in Cambodia and investigated their relationship with perceived learning outcomes. With the rapid advancement of digital technologies, AI tools are increasingly being integrated into students' academic activities, making it important to understand their potential impact on learning experiences.

The findings of this study indicate that university students in Cambodia demonstrate a moderate level of AI tool adoption, suggesting that many students are already incorporating AI technologies into their academic work. The results also show that students perceive moderately positive learning outcomes associated with the use of AI tools, indicating that AI technologies may support students in enhancing their understanding of course materials and improving the quality of their academic work.

Furthermore, the statistical analysis revealed a strong and significant relationship between AI tool adoption and perceived learning outcomes**.** The correlation analysis confirmed that students who adopt AI tools more frequently tend to report higher levels of perceived learning benefits. In addition, the regression analysis demonstrated that AI tool adoption significantly predicts perceived learning outcomes, explaining a substantial proportion of the variance in students' perceived learning experiences. These findings suggest that AI tools can serve as valuable learning assistants that support students' academic activities and contribute to improved learning outcomes when used appropriately.

Implications for the study

The implications of this study highlight the growing importance of integrating AI technologies into higher education. Universities should recognize the increasing use of AI tools by students and consider incorporating AI-related digital literacy into teaching and learning practices. Educators can guide students on how to use AI tools effectively while encouraging critical thinking and responsible use of AI-generated information. Establishing clear institutional policies regarding the ethical use of AI technologies can also help maintain academic integrity while allowing students to benefit from technological innovations.

Limitations and suggestions for future research

This study has several limitations. The analysis focused on the direct relationship between AI tool adoption and perceived learning outcomes and did not consider potential moderating variables such as gender, English proficiency, or digital literacy. These factors may influence how students use AI tools and perceive their learning outcomes.

Despite the contributions of this study, several opportunities remain for future research. Future studies may explore additional factors influencing AI adoption in education, such as students' digital skills, attitudes toward AI technologies, and institutional support for technology integration. Researchers may also examine the impact of AI tools on actual academic performance rather than perceived outcomes, as well as conduct longitudinal studies to understand how AI-assisted learning evolves over time. Expanding research across multiple universities and educational disciplines may also provide a broader understanding of AI adoption in higher education within Cambodia and similar developing contexts.

References

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology acceptance model in m- learning context: A systematic review. Computers & Education, 125, 389–412.

Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the era of generative artificial intelligence: Implications of ChatGPT. Education and Information Technologies, 1–15.

Biggs, J., & Tang, C. (2011). Teaching for quality learning at university (4th ed.). Maidenhead: Open University Press.

Bond, M., Bedenlier, S., Marín, V. I., & Händel, M. (2020). Emergency remote teaching in higher education: Mapping the first global online semester. International Journal of Educational Technology in Higher Education, 17(44), 1–24. https://doi.org/10.1186/s41239-020-00209-x

Bryman, A. (2016). Social research methods (5th ed.). Oxford University Press.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. IEEE Access, 8, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 1–12. https://doi.org/10.1080/14703297.2023.2190148

Crawford, J., Butler-Henderson, K., Rudolph, J., & Glowatz, M. (2020). COVID-19: 20 countries' higher education intra-period digital pedagogy responses. Journal of Applied Learning & Teaching, 3(1), 1–20. https://doi.org/10.37074/jalt.2020.3.1.7

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, 16(3), 297–334.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... (2023). Opinion paper: So what if ChatGPT wrote it? International Journal of Information Management, 71, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Eom, S. B., & Ashill, N. (2016). The determinants of students' perceived learning outcomes and satisfaction in university online education. Decision Sciences Journal of Innovative Education, 14(2), 185–215. https://doi.org/10.1111/dsji.12097

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American Journal of Theoretical and Applied Statistics, 5(1), 1–4.

Field, A. (2018). Discovering statistics using IBM SPSS statistics (5th ed.). Sage.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage.

Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.

Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of artificial intelligence in education. Computers and Education: Artificial Intelligence, 1, 100001. https://doi.org/10.1016/j.caeai.2020.100001

Joshi, A., Kale, S., Chandel, S., & Pal, D. (2015). Likert scale: Explored and explained. British Journal of Applied Science & Technology, 7(4), 396–403.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. Information & Management, 43(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Kuo, Y. C., Walker, A. E., Belland, B. R., & Schroder, K. (2014). A predictive study of student satisfaction in online education programs. International Review of Research in Open and Distributed Learning, 15(1), 16–39. https://doi.org/10.19173/irrodl.v15i1.1651

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. (2016). Intelligence unleashed: An argument for AI in education. Pearson.

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.

Rasiah, R., et al. (2022). Digital transformation in Southeast Asian higher education. Asian Journal of University Education, 18(2), 1–15.

Resnik, D. B. (2018). The ethics of research with human subjects. Cham: Springer.

Richardson, J. C., Maeda, Y., Lv, J., & Caskurlu, S. (2017). Social presence in online learning: A meta-analysis. Computers & Education, 117, 66–82. https://doi.org/10.1016/j.compedu.2017.06.007

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). New York: Free Press.

Russell, S., & Norvig, P. (2021). Artificial intelligence: A modern approach (4th ed.). Pearson.

Sun, P. C., Tsai, R. J., Finger, G., Chen, Y. Y., & Yeh, D. (2008). What drives successful e-learning? Computers & Education, 50(4), 1183–1202. https://doi.org/10.1016/j.compedu.2006.11.007

Tabachnick, B. G., & Fidell, L. S. (2013). Using multivariate statistics (6th ed.). Pearson.

Tarhini, A., Hone, K., & Liu, X. (2017). Factors affecting students' acceptance of e-learning environments in developing countries. Computers in Human Behavior, 72, 44–56. https://doi.org/10.1016/j.chb.2017.01.017

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. Computers & Education, 57(4), 2432–2440. https://doi.org/10.1016/j.compedu.2011.06.008

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending UTAUT. MIS Quarterly, 36(1), 157–178.

Wright, K. B. (2005). Researching internet-based populations: Advantages and disadvantages of online survey research. Journal of Computer-Mediated Communication, 10(3), 1–13.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education, 16(39), 1–27. https://doi.org/10.1186/s41239-019-0171-0

Heng, K., & Doeur, B. (2022). Digital transformation in higher education: Key to enhancing Cambodia's higher education sector. Cambodian Journal of Educational Research, 2(1), 146-156.

Sol, K., Heng, K., & Sok, S. (2025). Using ai in English language learning: An exploration of Cambodian efl university students' experiences and perceptions. Journal of Science of Learning and Innovations, 1(1), 1-32.

Sok, S., Heng, K., & Pum, M. (2025). Investigating high school students' attitudes toward the use of AI in education: Evidence from Cambodia. Sage Open, 15(3), 1-15.

Hoeurng, H., Phorn, P., Kheav, S., & Sam, R. (2024). Integrating artificial intelligence in higher education: A case study of Cambodian universities. European Journal of Theoretical and Applied Sciences, 2(5), 462-473.

Tao, N. (2026). Exploring Cambodian EFL university students' AI literacy and experiences: A qualitative analysis. Cambodian Journal of Educational Research, 6(1), 1-28.

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