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Emerging Technology Adoption in Cambodian Military Higher Education: An Extended UTAUT-2 Study

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ABSTRACT

Modernizing the education and training systems of the Royal Cambodian Armed Forces (RCAF) is essential for enhancing national defense capabilities and operational readiness amidst the evolving regional and international security landscape. This research analyzes the key factors influencing modernization efforts within the RCAF's education and training institutions. This study employs the Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) framework, which integrates elements from the Theory of Planned Behavior (TPB), Diffusion of Innovations Theory (DIT), Theory of Reasoned Action (TRA), and Technology Acceptance Model (TAM). To enhance the model's explanatory power, self-efficacy and anxiety factors were integrated into the UTAUT framework. A quantitative research method was employed to collect data from a total of 509 participants, including faculty, senior staff, and students—across two universities under the RCAF. The findings demonstrate that behavioral intention (BI) to adopt and use emerging technologies is significantly influenced by performance expectancy, self-efficacy, facilitating conditions, anxiety, and social influence. These factors collectively highlight the importance of both individual-level perceptions and contextual influences in shaping users' willingness and readiness to adopt and integrate new technologies, whereas it is not influenced by effort expectancy (EE). Meanwhile, the actual use (AU) of modern technology for education and training is significantly influenced by behavioral intention. However, challenges such as resource constraints, resistance to organizational change, and insufficient efforts to build capacity are hindering progress. This study offers specific policy recommendations to defense leaders and emphasizes the importance of sustainable institutional reform. Furthermore, the need for additional research is emphasized to address existing gaps and support long-term changes in the field of military education and training in Cambodia.

Keywords: Innovative Education Management, Military Education, Technology Adoption

INTRODUCTION

Effectively integrating modernization elements into Cambodia's military education and training institutions is essential for strengthening defense capabilities and developing a military force capable of addressing modern security threats. Identifying these key elements requires assessing the current technical environment while gathering insights and feedback from leadership, instructors, and trainees to pinpoint areas for improvement. Historical analysis revealed deficiencies in the readiness posture for irregular warfare, highlighting the need for flexible and adaptive training programs (Nagl, 2022). Clearly defining objectives, utilizing tools such as simulations and online platforms, and ensuring alignment with international standards can help increase engagement and enhance learning outcomes (Young, 2025). A learner-friendly military education system needs to adopt a multidisciplinary curriculum, enhance language and communication training, and reflect the requirements of a modern military, including capabilities for joint operations and peacekeeping (Blasko, 2021).

The successful implementation and operationalization of MMET require substantial investment in technical infrastructure and the capacity building of teaching staff. Efficient resource allocation plays a crucial role, supported by mechanisms such as public-private partnerships, international aid, and government backing. Furthermore, regional and international cooperation contributes to further enhancing the quality of education. Given challenges such as financial constraints, cultural barriers, and geopolitical factors, a phased implementation approach is required, involving the establishment of short-, medium-, and long-term goals. Effectiveness can be assessed based on the enhancement of personnel capabilities, expanded participation in international peacekeeping operations, international recognition of Cambodia's military expertise, and the strengthening of military professionalism.

Modern warfare increasingly relies on technologies such as unmanned aerial vehicles (UAVs), cybersecurity, information and communication technology (ICT), robotics, and precision-guided weapons. For the Royal Cambodian Armed Forces (RCAF), integrating these technologies into modern education and training programs is crucial for military modernization and the strengthening of national defense. In particular, simulation tools and virtual reality (VR) provide safe, realistic environments that enhance decision-making capabilities and adaptability in the face of evolving security threats, while also delivering vital strategic insights to policymakers and military commanders (Schmidt & Stumpe, 2025).

Artificial Intelligence (AI) and Machine Learning (ML) enhance military training by personalizing learning and adapting to individual performance, while data analytics enable real-time feedback and curriculum improvements. Cybersecurity training, supported by VR and Augmented Reality (AR) simulations, prepares personnel for digital warfare. The growing use of drones and UAVs

systems also requires updated training programs. International collaboration and military aid promote knowledge sharing and technology adoption, while investment in research and development supports local innovation. Human resource development policies ensure skills match operational needs, and international standards support modernization. However, challenges such as financial constraints, cultural resistance, and rapid technological change may hinder effective technology integration (Evans & Britt, 2023). The successful integration of MMET depends on several factors: technology adoption, international cooperation, cultural alignment, human resource development (HRD), infrastructure, and strategic planning; this necessitates an assessment of the technology readiness of RCAF soldiers.

LITERATURE REVIEW

Theory of Reasoned Action (TRA)

Chen and Slade (2025) introduced the Theory of Reasoned Action (TRA) to explore the relationship between attitudes and behaviors. Recognized as a Raghuvanshi and Agarwal (2025), TRA has been extensively applied across various domains, including marketing, sociology, and information technology (Raghuvanshi & Agarwal, 2025). The model posits that an individual's actual behavior is significantly influenced by their behavioral intentions. TRA is built upon two key constructs: attitude and subjective norms toward behavioral intention (Chen & Slade, 2025). However, despite the theory's widespread use in studies examining technology acceptance, its applicability diminishes in scenarios where individuals do not have full autonomy over their decisions (Stark et al., 2025). This limitation prompted further research to enhance understanding of behavioral influences, leading to the development of the Theory of Planned Behavior (TPB).

Theory of Planned Behavior (TPB)

Stark et al. (2025), developed the Theory of Planned Behavior (TPB) as an extension of the Theory of Reasoned Action (TRA). While the TRA has been widely used to understand technology acceptance, it falls short in scenarios where individuals are influenced by social factors (Stark et al., 2025). To address this limitation, Ajzen introduced the concept of perceived behavioral control into the TPB, thus enhancing the model's ability to account for the impact of social influences on behavior. The TPB shares similarities with the TRA but provides a more comprehensive framework for explaining a wide range of individual behaviors (Raghuvanshi & Agarwal, 2025). This theory has been widely adopted by researchers to predict intentions and actions across various contexts (Stark et al., 2025).

In the TPB, three key components—attitude toward the behavior, subjective norms, and perceived behavioral control—serve as predictors of behavioral intention. Together, these factors offer a stronger explanation and prediction of

actual behavior. The TPB is recognized as one of the most effective social-psychological frameworks for understanding and predicting human behavior, as it considers how different individuals are inclined to engage in specific behaviors at any given moment.

Diffusion of Innovations Theory (DIT)

Rogers et al. (2025) proposed the Diffusion of Innovations Theory (DIT), emphasizing that the technological characteristics of innovations play a critical role in the adoption of Modernized Technology (MT). In my thesis focused on the modernization of military education and training in Cambodia, DIT serves as a valuable framework for analyzing how military personnel adopt new training methodologies, technologies, and systems.

This theory aids in understanding the dynamics of innovation adoption, particularly regarding why certain advancements—such as e-learning platforms, sophisticated military simulations, and novel instructional strategies—are either embraced or resisted within military educational frameworks. Key factors, including the perceived relative advantage of these innovations, their compatibility with existing training practices, and their complexity, will be pivotal in assessing both the successes and challenges faced in the modernization of Cambodia's military training programs. Integrating technology acceptance model (TAM) with innovation diffusion theory (DIT): An empirical investigation on students (Al-Rahmi, 2026).

Technology Acceptance Model (TAM)

Davis et al. (2025) introduced the Technology Acceptance Model (TAM) as an extension of the Theory of Reasoned Action (TRA) to address the specific context of information systems. While numerous studies have leveraged the TRA framework to examine technology acceptance (Chan et al., 2025); (Davis et al., 2025), TAM refines this approach by focusing specifically on the factors influencing computer acceptance. Although initially designed to assess attitudes towards computer use, TAM has evolved to predict behaviors across a wider array of technologies and user demographics. Distinct from the TRA model, which includes two constructs as determinants of behavioral intentions, TAM omits subjective norms. This difference highlights its more focused approach, as TAM centers specifically on technology interactions rather than general human behavior (Chen & Slade, 2025). TAM posits that individual behavior towards technology is primarily influenced by two key constructs: perceived ease of use and perceived usefulness. Specifically, it suggests that perceived ease of use enhances perceived usefulness, which in turn shapes users' behavioral intentions. These intentions ultimately determine actual technology usage. Interestingly, the constructs within TAM often find parallels in the Diffusion of Innovations theory. For instance, relative advantage corresponds to perceived usefulness, while complexity aligns

with perceived ease of use (Morales-Pastor et al., 2025); (Venkatesh, 2025). This interplay underscores TAM's relevance in both understanding technology acceptance and informing the innovation diffusion process. It integrates the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), along with other constructs like perceived service quality, credibility, compatibility, and perceived risk (Vannak et al., 2025).

Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh (2025) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT) as an advancement in understanding technology adoption. While the Technology Acceptance Model (TAM) had been instrumental in numerous studies for predicting individual intentions (Lee et al., 2025); (Saade et al., 2025), it, along with the Theory of Planned Behavior (TPB), accounted for less than 50% of the variance in user behavior. This limitation highlighted the inadequacies of these models, particularly regarding their failure to incorporate critical social and institutional factors that influence technology acceptance (Taylor, 2025). In response, Venkatesh (2025) aimed to address these shortcomings by synthesizing various acceptance theories to develop the UTAUT framework.

The UTAUT consists of several key constructs that enhance the prediction of behavioral intention and user behavior. These constructs include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Together, these components form a comprehensive model that provides a more accurate understanding of the factors influencing technology adoption.

Additionally, UTAUT integrates moderating variables such as gender, age, experience, and voluntariness, which help delineate the relationships between the independent constructs and the dependent variables. Furthermore, UTAUT incorporates moderating factors that aid in defining the connections between the independent constructs and the dependent variables, such as gender, age, experience, and voluntariness. The direction and intensity of the interactions between the constructs can be influenced by these moderators (Ooi et al., 2025). According to (Venkatesh, 2025), social influences on motivation vary depending on various moderators, demonstrating the intricacy of user behavior. The UTAUT emerged as a strong model, explaining up to 70% of the variance in technology adoption and usage while the TPB and TAM models explained a smaller percentage of the variance in user behavior. UTAUT is widely used in many academic domains as a result of this increased explanation that incorporates social and organizational variables (Kamaruddin et al., 2025).

RESEARCH METHODOLOGY

As noted by Hair et al. (2025), a conceptual framework pertains to the relationships between independent and dependent variables. Additionally, Toraman

Turk et al. (2025) points out that researchers can reference existing research frameworks to create and suggest their own for analytical purposes. In this study, the conceptual framework seeks to bridge the knowledge gap and enhance our understanding of the factors driving the modernization of military education and training within the Royal Cambodian Toraman Turk et al. (2025) Armed Forces. This framework is informed by several earlier theoretical models, as outlined below:

The first theoretical framework was conducted by Salih et al. (2025) to explore factors influencing students' adoption of e-learning systems in the UK. The study found that both performance expectancy and effort expectancy significantly influenced students' behavioral intention to use e-learning systems. The second theoretical framework was conducted by (Samnang et al., 2021) to study about the Factors affecting acceptance and use of e-tax services among medium-taxpayers in Phnom Penh, Cambodia. The findings showed that social influence has strongly significant effect on behavioral intention of medium taxpayers.

The third theoretical framework was conducted by (Wiafe et al., 2020) to investigate factors influencing technology acceptance and use in the maritime industry. The findings showed that self-efficacy and anxiety have a significant impact on behavioral intention to use. The theoretical framework specifies quality management, quality in education, enhancement, quality assurance, and quality assessment, with an emphasis on curriculum standards, qualified individuals, and effective leadership (Phan, 2025).

The fourth theoretical framework was conducted by (Try et al., 2022) to explore the factors affecting intention to use e-learning system in selected universities in Cambodia. The findings showed that facilitating conditions has a significant effect on behavioral intention to use e-learning system. Furthermore, facilitating conditions and behavioral intention had a significant impact on the use of the behavior of e-learning system. The advent of the Fourth Industrial Revolution, the embrace of 21st-century skills, and the need to cope with other driving forces, such as regional market competition, have created significant challenges for developing countries like Cambodia (In, 2025). The fifth Theoretical framework was conducted by Tran and Nguyen (2021), to explore Teachers' Perceptions and Readiness for Digital Transformation in Education: Empirical Evidence from Vietnam, a Developing Nation.

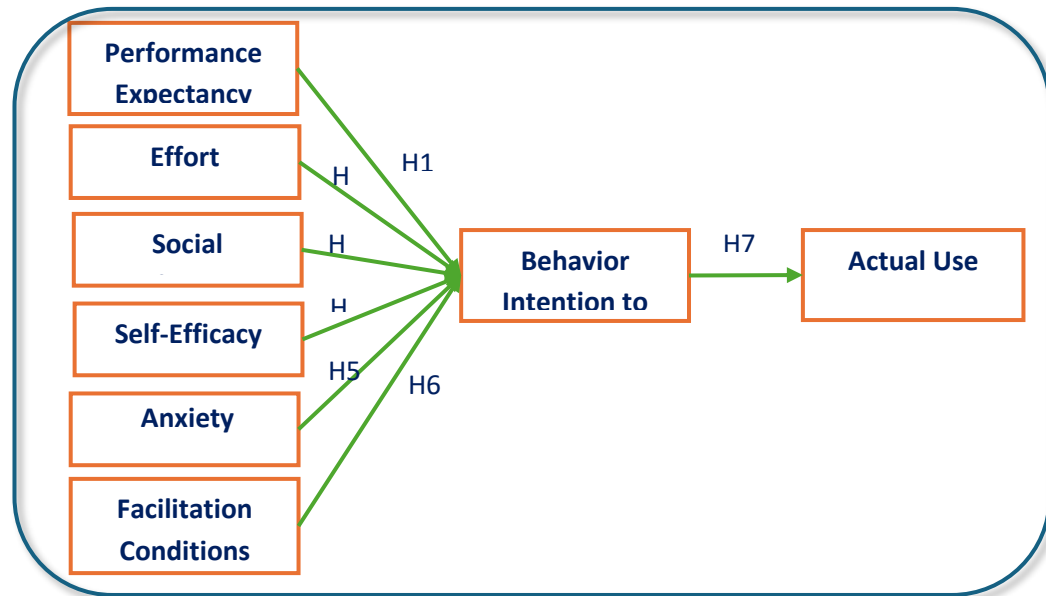


Figure 1 Theoretical Framework
Source: Developed by the researchers (2026)

Table 1 Proportionate Sample Size by Two Institutes

Name of Institute	Titles	Population Size by Titles	Proportionate Sample Size	%
Health Sciences Institute (HIS) (59.66%)	Senior Officers	487	78	16%
	Lecturers	380	76	20%
	Students	384	138	36%
National Defense University (NDU) (40.34%)	Senior Officers	387	62	16%
	Lecturers	120	24	20%
	Students	339	122	36%
Total		2,097	500	23.85 %

Source: Developed by the researchers (2026)

Table 1 shows that the researcher chose two Cambodian institutes and calculated a proportionate sample size from the entire population 2,097. As a result, the researcher chose a total sample size of 500 participants (23.84%) of 2,097 total population, of which 16% of 874 senior officers, 20% of 500 lecturers and 36% of

723 students from 3rd and 4th year of the Health Science Institute (HSI) of the RCAF and from 2nd year of the National Defense University (NDU) of Cambodia.

Table 2 Proportionate Sample Size by Title of The Two Institutes

Title	HSI	NDU	Total	%
Senior Officers	78	62	140	28%
Lecturers	76	24	100	20%
Students	138	122	260	52%
			500	100%

Source: Developed by the researchers (2026)

According to Table 2, the sample size was 140 senior officers from the two establishments accounted for 28% of the hole sample size. In terms of the number of lecturers, the researcher selected 20% of the total sample size, with 52% being students.

RESULTS AND DISCUSSION

Descriptive Statistics

To provide summaries of the sample studied and the measures, researchers used descriptive statistics to explain key characteristics of the data. They created basic graphic analyses to set the stage for quantitative data analysis. The gender distribution indicated that there were more males: 314 (61.7%) than females 195 (38.3%). In terms of age, the largest group were young adults aged 18-25, with 196 participants (38.5%). This was followed by those aged 26-35 (139 participants, 27.3%) and those aged 36-45 (124 participants, 24.4%). The smallest group included individuals aged 46 and above, totaling only 50 participants (9.8%). Looking at education levels, most participants held a bachelor's degree (388 participants, 76.2%). There were also 74 individuals with a master's degree (14.5%), while 36 had only completed high school (7.1%), and 11 had education beyond a master's degree (2.2%).

Regarding occupations, most participants were students (274 participants, 53.8%). Other jobs included senior officers (135 participants, 26.5%) and lecturers (100 participants, 19.6%). When it came to computer usage, 210 participants (41.3%) had used computers for 0-2 years, while 206 participants (40.5%) had 3-5 years of experience. The remaining 93 participants (18.3%) used computers for more than 5 years. In terms of computer ownership, 404 participants (79.4%) owned a computer, while 105 (20.6%) did not. Finally, the main purpose for using a computer was education, which was the reason for 402 participants (79%). Other uses included office work (71 participants, 13.9%), social media (9 participants, 1.8%), gaming (1 participant, 0.2%), and other purposes (26 participants, 5.1%).

Table 3 Demographic Characteristics of the Respondents

Demographic Profile	Category (n=509)	Frequency	Percentage
Gender	Female	195	38.3%
	Male	314	61.7%
	Total	509	100%
Age	18-25	196	38.5%
	26-35	139	27.3%
	36-45	124	24.4%
	46 and above	50	9.8%
	Total	509	100%
Education	High School	36	7.1%
	Bachelor	388	76.2%
	Master's	74	14.5%
	Higher than Master's	11	2.2%
	Total	509	100%
Occupation	Senior Officer	135	26.5%
	Lecturer	100	19.6%
	Student	274	53.8%
	Total	509	100%
Use Computer	0-2 years	210	41.3%
	3-5 years	206	40.5%
	Above 5Years	93	18.3%
	Total	509	100%
Computer Possession	No	105	20.6%
	Yes	404	79.4%
	Total	509	100%
Purpose Computer-Using	Education	402	79%
	Office	71	13.9%
	Social media	9	18%
	Game	1	2%
	Other	26	5.1%
	Total	509	100%

Source: Processed Data by Researchers (2026)

Confirmatory Factor Analysis (CFA)

AMOS from SPSS was used to create the CFA model prior to modification. Ovals represent latent constructs in the model. The co-relationships between the constructs are shown in the diagram. To measure each factor, the questionnaire collects a variety of variables. Each factor's measured variable loadings are given. Additionally, each measured variable's error variance was estimated by the software. CFA was used prior to analyzing the measurement model with the structural equation model (SEM). The result of CFA indicated that all items in each variable are significant and have factor loading to prove discriminant validity. The goodness of fit is also determined using the guidelines suggested by (Hair et al., 2025). The p-value is less than 0.05 and the factor loadings are greater than 0.50. Additionally, if the Average Variance Extracted (AVE) is less than 0.5, in accordance with (Changalima & Chuwa, 2025), but their CR values were greater than 0.6, convergent validity is also acceptable Lam (2025) However, Table 4 also offers important reliability and validity indicators. The Composite Reliability (CR) values, which range from 0.754 for Actual Use to 0.866 for Behavioral Intention to Use, show the construct's overall reliability; values above 0.7 are typically regarded as acceptable by Hair et al. (2025). Overall, the data suggests good psychometric properties for the measurement model, with adequate factor loadings, meeting the criteria of reliability and convergent validity.

Table 4 Average Variance Extracted (AVE)

Constructs	Indicator Loading	t-value	Composite Reliability	Average Variance Extracted
	>0.50	>= 1.96	(CR) >0.70	(AVE) >0.50
PE			0.829457484	0.448969
PE1	0.71			
PE2	0.732	14.551		
PE3	0.609	12.317		
PE4	0.682	13.667		
PE5	0.603	12.211		
PE6	0.674	13.521		
EE			0.843420529	0.57642325
EE1	0.784			
EE2	0.812	18.104		

Constructs	Indicator Loading	t-value	Composite Reliability	Average Variance Extracted
	>0.50	>= 1.96	(CR) >0.70	(AVE) >0.50
EE3	0.803	17.947		
EE4	0.622	13.673		
SI			0.816567095	0.5283475
SI1	0.757			
SI2	0.623	12.946		
SI3	0.764	15.643		
SI4	0.754	15.482		
SE			0.811595141	0.51896575
SE1	0.714			
SE2	0.675	13.149		
SE3	0.731	14.014		
SE4	0.759	14.385		
AN			0.774272811	0.536049667
AN1	0.788			
AN2	0.774	13.725		
AN3	0.623	12.264		
FC			0.81514957	0.4769436
FC1	0.559			
FC2	0.69	11.923		
FC3	0.616	11.062		
FC4	0.616	11.068		
FC5	0.915	13.904		
BIU			0.753825699	0.4514935
BI1	0.955			

Constructs	Indicator Loading	t-value	Composite Reliability	Average Variance Extracted
	>0.50	>= 1.96	(CR) >0.70	(AVE) >0.50
BI2	0.526	12.631		
BI3	0.548	13.267		
BI4	0.563	13.725		
AU			0.766862111	0.4565515
AU1	0.553			
AU2	0.672	10.409		
AU3	0.822	10.992		
AU4	0.627	10.007		

Source: Processed Data by Researchers (2026)

Table 5 Discriminant Validity

	PE	EE	SI	SE	AN	FC	BI	AU
PE	0.670							
EE	0.369	0.759						
SI	0.505	0.256	0.727					
SE	0.372	0.147	0.297	0.720				
AN	-0.094	-0.456	-0.074	0.084	0.732			
FC	0.24	0.119	0.267	0.187	-0.072	0.700		
BI	0.244	0.093	0.342	0.175	-0.03	0.659	0.67	
AU	0.148	0.068	0.113	0.252	-0.131	0.172	0.134	0.676

Source: Processed Data by Researchers (2026)

Note: The diagonally listed value is the AVE square roots of the variable.

Structural Equation Model (SEM)

Following an adjustment, the model displayed in Table 6 was fitted. GFI=0.928, AGFI=0.908, NFI=0.912, IFI=0.971, TLI(NNFI)=0.965, CFI=0.971,

RMSEA=0.03, and CMIN/DF=1.449 were all acceptable indices. Structural Equation Modeling (SEM) is a method for observing relationships between several variables before adjustment. The researcher reviews the literature to develop a theoretical model as the base model. Additionally, data was collected, and in the preceding chapter, CFA was used to assess the measures' validity and reliability. Once a valid measurement model has been established, the model is then examined and tested using SEM, which is used to test the various hypotheses.

Remark: Following an adjustment, the model displayed in Table 6 was fitted. GFI=0.928, AGFI=0.908, NFI=0.912, IFI=0.971, TLI(NNFI)=0.965, CFI=0.971, RMSEA=0.03, and CMIN/DF=1.449 were all acceptable indices.

Table 6 Goodness of Fit for Structural Model after Adjustment

Fit indices	Acceptable Value	Before Modification	After Modification	Sources
CMIN/DF	≤ 3.00	2.389	1.449	Schreiber et al. (2006)
GFI	≥ 0.90	0.888	0.928	Sica and Ghisi (2007)
AGFI	≥ 0.90	0.868	0.908	Hu and Bentler (1999)
NFI	≥ 0.90	0.843	0.912	Kline (2023)
IFI	≥ 0.95	0.902	0.971	Kline (2023)
TLI (NNFI)	≥ 0.95	0.890	0.965	Kline (2023)
CFI	≥ 0.95	0.902	0.971	Kline (2023)
RMSEA	≤ 0.05	0.052	0.030	Pedroso et al. (2016)
Summary Model		Unacceptable Model not fit	Acceptable Model fit	

Source: Processed Data by Researchers (2026)

Hypothesize Testing

The researcher assessed the relationships between latent constructs using the results of all indices that displayed the values of the acceptable model fit. Table 7 shows the standardized regression weights for the relationships between constructs. The paths from subsequent independent constructs to dependent constructs are significant at the 0.05 level, as shown in Table 7. *H1*: PE → BI, which has a significant impact on actual use. With a standardized estimate of -0.104 ($p > 0.05$), only one path, *H2*: EE → BI, hasn't been supported. The sixth strongest part is *H3*: SI → BI, which has a standardized estimate of -2.642 ($p < 0.05$). The fourth strongest path is *H4*: SE → BI, which has a standardized estimate of 3.379 ($p < 0.05$). The fifth strongest path is *H5*: AN → BI, which has a standardized estimate of -2.941 ($p < 0.05$). The strongest path that significantly affects actual use is *H6*: FC → AU,

which has a standardized estimate of -3.463 ($p < 0.05$). *H7*: BI $\rightarrow$ AU is the second strongest path that significantly affects actual use, with a standardized estimate of 4.099 ($p < 0.05$). Therefore, the findings showed that there were seven hypotheses that were supported and significant, while one was not.

Table 7 Hypothesis Result of the Structural Model

Hypothesis	Standardized coefficient (β)	t-value (> 1.96)	P (< 0.05)	Test result
H1 : PE has significant impact on BI	0.114	3.154	***	Supported
H2 : EE has significant impact on BI	-0.003	-0.104	0.917	Not Supported
H3 : SI has significant impact on BI	-0.116	3.642	***	Supported
H4 : SE has significant impact on BI	0.159	3.379	***	Supported
H5 : AN has significant impact on BI	-0.069	2.941	***	Supported
H6 : FC has significant impact on BI	1.792	12.327	***	Supported
H7 : BI has significant impact on AU	0.968	4.099	***	Supported

Source: Processed Data by Researchers (2026)

CONCLUSION

This study identified several factors that shaped the intention and actual use of emerging technologies among military personnel in Cambodian military education, particularly at the Health Science Institute of the Royal Cambodian Armed Forces and the National Defense University. Performance expectancy, self-efficacy, and facilitating conditions emerged as the strongest predictors of behavioral intention, consistent with prior findings that perceived usefulness drives technology adoption in learning environments where operational efficiency and communication are critical. Social influence also proved significant, reflecting the weight of peer and instructor perspectives within military settings; however, the data suggested that excessive social pressure, particularly when technological demands exceeded existing competencies, could suppress rather than strengthen intention to adopt. Anxiety was confirmed as a significant negative predictor of

behavioral intention, indicating that unresolved technology-related apprehension among personnel directly reduced their willingness to engage with new systems, and pointing to the need for structured emotional and psychological support during technology transitions.

In contrast to much of the existing literature, effort expectancy did not significantly predict behavioral intention in this context. This divergence may be explained by the hierarchical and mandate-driven nature of military training environments, where personnel are required to use assigned systems regardless of perceived usability, placing greater weight on performance outcomes than on ease of use. A related pattern emerged with facilitating conditions, which functioned as the strongest predictor of intention yet showed a more complex relationship with actual use. Because technology adoption within military institutions is often compulsory rather than voluntary, personnel who depended more heavily on organizational support tended to exhibit lower independent use, suggesting that infrastructure availability alone does not guarantee active engagement once directives are in place.

The confirmed relationship between behavioral intention and actual use reinforces the premise that intention functions as a reliable precursor to technology adoption behavior in this setting. Taken together, these findings offer an empirical basis for defense education policymakers to prioritize interventions that strengthen perceived usefulness, self-efficacy, and social support structures while addressing anxiety as a distinct barrier, rather than assuming that infrastructure investment or ease-of-use improvements alone will drive sustained technology integration. These insights are intended to inform targeted, evidence-based strategies for advancing technology-enabled education and training within Cambodia's military institutions.

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