Critical Thinking and Students' Intentions to Use Artificial Intelligence Chatbots for Learning: Evidence from Vietnamese Universities

My-Duyen Thi Nguyen and Diep-Ngoc Le *

University of Education, Vietnam National University, Hanoi, Vietnam
Email: ntmd241103@gmail.com (M.-D.T.N.); lediep@vnu.edu.vn (D.-N.L.)
*Corresponding author

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***Abstract*—Artificial Intelligence (AI) chatbots are increasingly reshaping learning practices in higher education. This study extends the Technology Acceptance Model (TAM) by incorporating critical thinking as a key cognitive antecedent of behavioral intention to use AI chatbots for learning. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), data collected from Vietnamese university students (*n* = 100) were analyzed to examine the proposed relationships. The findings indicate that critical thinking is predictively associated with students' self-reported behavioral intention to use AI chatbots and shows a larger standardized association than traditional TAM factors, including perceived usefulness, perceived ease of use, and attitude. Attitude toward AI chatbot use also directly predicts behavioral intention and is positively associated with critical thinking, suggesting a potential mediation mechanism. The extended model demonstrates substantial explanatory power in explaining variance in students' self-reported behavioral intention. Overall, the results highlight critical thinking as an important cognitive factor associated with more reflective and responsible use of AI chatbots in university education. Given the cross-sectional and exploratory design, the findings should be interpreted as predictive rather than causal.**

***Keywords*—artificial intelligence, critical thinking, generative artificial intelligence, technology acceptance model, Vietnam**

I. Introduction

The rapid development of Generative Artificial Intelligence (GenAI), particularly AI chatbots represented by ChatGPT, is significantly changing the learning environment in global higher education [1–4]. In this context, many Vietnamese universities have gradually piloted the incorporation of these tools across teaching and learning activities in order to support greater autonomy among students [5]. Recent research has shown that users' engagement with such systems is shaped by a complex interplay of perceptual, cognitive, and experiential factors rather than by instrumental considerations alone. A comprehensive synthesis by Chen *et al*. [6]indicates that users' attitudes and intentions toward GenAI are often formed through holistic interaction experiences, including perceived fluency, responsiveness, and personal competence in using these technologies. While GenAI offers clear benefits for learning efficiency and performance, it also raises concerns regarding over-reliance, Critical Thinking (CT), and academic integrity [7]. At the same time, students report concerns regarding over-reliance on AI tools and potential threats to academic integrity, underscoring the need for a balanced and reflective approach to AI integration in higher education [8, 9].

Evidence from prior reviews in Vietnamese university education indicates that students generally associate the use of AI tools with improved learning performance, while at the same time expressing reservations about excessive reliance and its possible negative implications for CT [10]. As AI increasingly supports humans in performing different tasks, the risk of depending on machines for thinking may induce a decline in learners' ability to think and assess for themselves, especially when CT is lacking [11]. CT, widely recognized as a core competency in university education, enables learners to evaluate the accuracy, credibility, and potential biases of information generated by AI systems [12–14]. In the AI era, CT has been increasingly emphasized as a reflective and evaluative reasoning process that helps maintain intellectual autonomy and ensures that these technologies support rather than replace human reasoning in higher education [15]. Thus, the role of CT in shaping how students interact and make decisions when using AI chatbots is an issue that requires further investigation.

Currently, several international studies have begun to clarify the relationship between CT and the Behavioral Intentions (BI) to use AI chatbots [16, 17]. In addition, the Technology Acceptance Model (TAM) continues to play a fundamental role in explaining technology usage contexts [18]. However, relatively few studies have examined the integration of CT within the TAM framework. Recent research suggests that TAM can be meaningfully linked with higher-order cognitive constructs, such as CT, particularly in language learning contexts [19]. While the TAM has been widely applied to explain technology use intentions, its traditional emphasis on Perceived Usefulness (PU) and Perceived Ease of Use (PEU) as separable determinants may be less adequate for highly interactive systems such as GenAI. Chen *et al.* noted that in many recent studies, these perceptions tend to overlap conceptually and empirically, suggesting the need to reconsider how acceptance models are applied in GenAI contexts [6]. Prior studies have shown mixed findings regarding the role of PU in shaping students' intentions to use GenAI tools. For example, Cano and Nunez [20] reported that PU did not consistently predict students' intentions, whereas experiential factors showed stronger associations.

Despite these contributions, several key gaps remain. Firstly, there is a construct gap, as relatively few studies have explicitly integrated CT into the TAM to explain BI. Secondly, there is a modeling gap, given the inconsistent findings regarding the role of PU in shaping students' intentions to use GenAI tools. Thirdly, there is a contextual gap, as limited empirical evidence exists in the Vietnamese higher education context examining the relationship between CT and BI through an extended TAM framework. To the best of our knowledge, no prior study has simultaneously integrated CT into the TAM framework to examine students' BI to use AI chatbots in the Vietnamese university education context. To address these gaps, this study aims to explore the role of CT in shaping Vietnamese university students' BI to use AI chatbots. Based on the extension of TAM with the CT variable, the Partial Least Squares Structural Equation Modeling (PLS-SEM) is applied to evaluate the suitability of the extended model in the Vietnamese higher education context. In particular, the proposed research model conceptualizes how PU and PEU influence ATU, which in turn affects BI. In addition, CT is incorporated as a cognitive mechanism linking ATU and BI in the context of AI chatbot use. The study further seeks to clarify the relationships between CT and key TAM constructs, thereby providing empirical insights into the application of AI chatbots in university education. The study proposes the hypothesis that:

H1: PEU is expected to exert a positive effect on ATU.

H2: PU is expected to exert a positive effect on ATU.

H3: ATU is expected to exert a positive effect on BI.

H4: ATU is likely to have a positive impact on CT.

H5: CT is likely to have a positive impact on BI.

This study is expected to offer several contributions. From a practical perspective, it provides empirical insights to inform university-level AI policies, particularly in promoting responsible and balanced use of AI chatbots in learning environments. In terms of instructional design, it highlights the role of CT in guiding the effective integration of AI tools and supporting the development of pedagogical strategies that foster reflective and autonomous learning. From a theoretical standpoint, the study extends the TAM by incorporating CT as a higher-order cognitive construct, thereby contributing to the advancement of technology acceptance research in the context of GenAI. In addition, the study offers implications for promoting AI literacy and supporting academic integrity through more reflective and responsible engagement with AI.

II. LITERATURE REVIEW

A. Technology Acceptance and University Students' AI Chatbots Behavioral Intention to Use

The TAM proposed by Davis [18], is one of the foundational frameworks employed to explore users' acceptance of technology. In the TAM framework, Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are two key factors. In addition, a third factor, attitude, serves as a mediator and predicts the use of BI [18]. The model's broad applicability across diverse technologies and user groups explains its widespread acceptance, along with the increasing number of studies adopting TAM across various domains in general and within educational settings in particular [21].

Within higher education, the TAM model has demonstrated its suitability in explaining the factors that influence attitudes and technology use behavior in the context of many countries [21, 22]. In which the intention to use is a crucial determining factor in actual intention to use [23]. In Vietnam, studies have also applied the TAM model to examine students' technology adoption behavior in contexts such as online learning during the COVID-19 period. Thuy and Tuong [24] combined TPB and TAM to propose a logical framework for students' online learning behavior, indicating that PU and PEU have a positive influence on attitudes, which in turn affect the intention to use. Research with students at Dong Nai University found that both PU and PEU are related to the BI to use technology for online learning. Specifically, the support provided through the online learning system was evaluated positively by students. The level of interaction and the ease of use of the system were also positively assessed when guidance was available [25].

The emergence of generative artificial intelligence applications, such as ChatGPT, has led researchers to further adapt the TAM model for analyzing students' attitudes, acceptance, and behavioral intention. The PU has been shown to be the predictor of the BI to use ChatGPT [26]. Extensions of TAM have incorporated factors such as AI self-efficacy, trust, facilitating conditions, subjective norm, and intrinsic motivation to explain BI in GenAI contexts [26, 27]. Consistent with the study of [28], PU has connected with performance expectation, showing a positive attitude and the belief that ChatGPT is a useful tool for learning, helping students complete tasks more quickly, and improving their overall learning outcomes. For ChatGPT, the PEU is voiced through users' views that the tool is easy to relate to and does not require much technical knowledge [28]. Prior studies examining students' engagement with GenAI suggest that PU does not always function as a direct antecedent of BI. For instance, Cano and Nunez [20] found that PU did not significantly influence students' intention to use GenAI, challenging the traditional assumption of TAM that usefulness is a primary driver of BI.

Notably, in the context of interactive generative systems such as AI chatbots, the conceptual distinction between PU and PEU may require reconsideration. Unlike traditional systems, where PU and PEU are relatively separable [18, 21], GenAI systems support both interaction and task execution through natural language-based interfaces, allowing users to communicate with the system while performing various learning-related tasks [29–31], thereby linking interaction and task execution within a conversational interface and potentially reducing technical barriers and cognitive effort for users. As a result, users' PU may depend not only on system performance but also on their ability to critically evaluate and interpret AI-generated outputs [13, 32]. This suggests that traditional TAM constructs may not fully capture acceptance behavior in GenAI contexts, highlighting the need to incorporate higher-order cognitive factors, such as CT, to account for users' quality of judgment [9, 11, 15].

Taken together, these findings indicate that while TAM remains robust in explaining AI adoption, the relative importance of its core constructs may vary across technological phases, especially in the context of GenAI. However, existing findings remain somewhat inconsistent regarding the strength of relationships among PU, PEU, ATU, and BI in AI chatbot use. Therefore, this study re-examines TAM relationships to understand university students' use of AI chatbots. Specifically, PEU is expected to enhance users' attitudes toward GenAI by reducing cognitive effort, while PU is expected to strengthen ATU by increasing perceived performance benefits. This suggests that both PU and PEU play a critical role in shaping users' evaluative responses toward AI chatbots. In turn, a positive ATU is likely to translate into stronger BI, as favorable evaluations increase users' willingness to adopt the technology.

B. Critical Thinking and Its Role in the Use of AI

The rapid development of AI, particularly AI chatbots systems, is transforming the way humans access information and knowledge. In this context, the CT centered on the ability to analyze, evaluate, reason, and make evidence-based decisions has played a crucial role in ensuring that learners do not become passive recipients of the vast amount of information provided by AI [13]. The fast-growing emergence of AI chatbots systems, with ChatGPT as a prominent example, has brought both opportunities and challenges for cultivating CT. It has underscored the importance of CT as an essential competence for students to use AI tools effectively and responsibly [17]. Recent empirical evidence, Suriano *et al.* [32]suggests that through intentional and interactive use, actively prompting, evaluating, and iterating, students shift from passive reception to deliberate, higher-order thinking. This empirical evidence supports the argument that active, attitude-driven engagement with AI can trigger higher-order cognitive processes such as CT. In a study involving university students and instructors in the Middle East, Alshamy *et al.* reported that users' evaluations of GenAI were closely tied to contextual learning practices and interaction experiences rather than abstract assessments of technological utility [33].

Recent developments in educational AI have been argued to focus on integrating the computational capabilities of AI with the CT, analytical, and creative capacities unique to humans, rather than allowing technology to completely replace learners' cognitive activities [14]. Despite growing scholarly attention to strategies for fostering CT in AI-supported learning environments, most existing studies emphasize pedagogical or ethical frameworks rather than empirically testing behavioral models. Sitepu *et al.* [15] highlight this gap by showing that while numerous strategies have been proposed to enhance CT in the AI era, limited research has examined how CT functions as a predictive factor shaping students' intentions and behaviors when using AI tools. Empirical evidence suggests that the influence of AI chatbots on CT is contingent upon learners' modes of interaction. When students actively evaluate and select AI-generated information, CT may be stimulated; however, uncritical acceptance of system outputs has been associated with reduced motivation and diminished independent reasoning [16, 34, 35]. Therefore, raising awareness of the limitations, risks, and imperfections of AI has been identified as a crucial factor in enabling learners to maintain an active role in the learning and decision-making process [35].

For students, AI chatbots can personalize interactions and tailor assistance according to their needs, thereby enhancing knowledge acquisition and retention, improving the learning experience, and fostering overall academic performance [36]. Supporting this view, Slimi *et al.* [8] reported that students perceive AI integration in higher education as enhancing learning experiences through personalized support, timely feedback, and opportunities for engagement that may foster CT. However, their study primarily focuses on perceptions and attitudes, offering limited insight into how such attitudes translate into cognitive processing mechanisms such as CT during AI use. From a cognitive perspective, CT enables learners to actively evaluate, verify, and regulate AI-generated information rather than passively accepting it. In this sense, CT functions as a cognitive filter that helps students assess the reliability and appropriateness of AI outputs, and as a mechanism that prevents over-reliance, thereby supporting more informed and responsible BI [13, 13, 32]. This evaluative process is more likely to be activated when learners hold favorable ATU toward AI systems, as positive ATU can increase cognitive engagement and motivate deeper, more systematic processing of GenAI information, which constitutes a key condition for the activation of the CT. From a theoretical perspective, ATU are considered antecedents of cognitive engagement in technology use contexts, as they shape users' willingness to invest effort and process information more deeply [18, 37]. Positive ATU toward AI use may lead students to engage more actively and reflectively with AI-generated content, thereby increasing the likelihood of engaging in prompting, verifying, and iterative practices that activate CT [19, 32, 33]. The study by Esiyok *et al.* shows that AI chatbots can support learning by providing personalized feedback, guidance, and facilitating communication and assessment in educational contexts [38]. In summary, exploring AI chatbot for BI use in learning should not be limited to technical aspects but should also take into account learners' cognitive processes, particularly the role of CT as a cognitive driver of AI usage behavior. While prior extensions of TAM have emphasized users' confidence in operating AI systems and perceived social or institutional support [27], relatively little attention has been paid to learners' critical evaluation of AI outputs. This gap suggests the relevance of examining CT as a cognitive mechanism linking ATU toward AI chatbot to BI.

In the context of AI adoption in Vietnam, lower secondary school teachers highly value the necessity of AI applications in teaching, particularly their potential to support creativity, save time, and improve work efficiency [39]. Regarding university students and language learning, a recent study by Thai [5] has revealed that while most students are aware of ChatGPT, only a small number use it for language learning. Nevertheless, they positively evaluate its potential to support learning, including providing quick feedback and helping to improve skills. Students also have indicated concerns related to the reliability of information and the potential negative impact on CT if excessive reliance develops [5].

Moreover, the nature of learners' cognitive activities when using AI has also been shifting. Instead of directly constructing knowledge, learners have increasingly taken on the role of supervising, verifying, and adjusting the outputs generated by AI [34, 40]. The CT has been argued to require a higher level of thinking, which has involved not only analyzing information but also evaluating the relevance, reliability, and potential implications of the data [41]. While international evidence highlights both the opportunities and challenges that AI chatbots bring to CT, it is equally important to consider how these dynamics are demonstrated in specific local contexts such as Vietnam. The study by Giang *et al.* [42] has found that manifestations of CT have been only at an average level. Reasons identified by Hang *et al.* [43], including esteem for teachers in East Asian culture and a dislike of engaging in direct review, have been reported as factors affecting learners' CT. However, CT has been proven to positively impact students' problem-solving skills and enhance outcomes [44]. For that reason, to develop CT, the learning environment in Vietnamese universities has been suggested to need reducing the emphasis on knowledge acquisition and creating more opportunities for students to engage in dialogue and academic debate [45, 46]. In sum, both global and Vietnamese studies underscore that AI does not diminish the role of CT; it reinforces the urgent need to cultivate students' ability to use AI tools critically, responsibly, and effectively within higher education.

To summarize consistent findings, prior studies highlight the importance of CT in shaping learners' engagement with AI tools. However, the role of CT as a predictive factor in behavioral models of AI adoption remains underexplored, particularly in relation to ATU and BI. From a cognitive perspective, a favorable ATU is likely to increase users' engagement and motivate deeper evaluation of AI-generated content, thereby activating CT. In turn, CT enables users to assess the reliability and usefulness of AI outputs, thereby enhancing their confidence and BI in using such systems. Therefore, this study examines CT as a cognitive mechanism linking ATU and BI.

Building upon the established relationships within TAM, this study extends the model by incorporating CT as an additional cognitive dimension. This extension aims to provide a more comprehensive understanding of how students interact with AI chatbots in educational settings, particularly in terms of critical thinking and higher-order cognitive processes.

III. Materials and Methods

A. Research Design

Informed by the TAM, the relationship between CT and students' BI to use AI chatbots for learning was examined using a quantitative cross-sectional survey. Data were collected through a questionnaire consisting of measurement scales adapted from established studies in TAM and AI adoption literature and modified to fit the context of Vietnamese university students. The questionnaire included statements measured on a Likert scale (5-point) or refined based on scales from prior research. The questionnaire was translated into Vietnamese using a back-translation procedure and reviewed by domain experts to ensure clarity and content validity (see Table 1).

Table 1. Measurement scales

Construct(s)			Resources
Perceived Usefulness (PU)	PU1	AI chatbots enable me to locate relevant information efficiently	[17]
	PU2	AI chatbots support my understanding of complex concepts in the learning process	
	PU3	AI chatbots increase my study efficiency by providing timely responses	
Perceived Ease of Use (PEU)	PEU1	The interface of AI chatbots is easy to understand	
	PEU2	I find it easy to access and use AI chatbots for the learning process needs	
	PEU3	The instructions provided by AI chatbots are clear and easy to follow	
Attitude toward Using AI chatbots (ATU)	ATU1	Using AI chatbots to build outlines, organize, and expand ideas	
	ATU2	Using AI chatbots to support essays and academic research	
	ATU3	Using AI chatbots as a virtual assistant helps me clarify questions related to my lessons	
Behavioral Intention to Use of AI Chatbots (BI)	BI1	When exploring a new topic, using AI chatbots stimulates me to study the subject more deeply	
	BI2	I plan to use AI chatbots to support tasks such as generating ideas, drafting content, or preparing scripts for educational purposes	
	BI3	I plan to use AI chatbots as a supportive tool to enhance my learning, rather than as a substitute for my own independent thinking	
Critical Thinking in the Using AI chatbots (CT)	CT1	I verify the information from AI chatbots with multiple sources to ensure accuracy	[32, 47]
	CT2	I prompt AI chatbots to provide credible sources and evidence	
	CT3	I ask questions and demand responses from AI chatbots from multiple perspectives	

B. Sample and Data Collection

A non-probability convenience sampling technique was employed, targeting students enrolled at the University of Education, Vietnam National University, Hanoi, who had prior experience with or interest in using AI chatbots for learning. Data were collected online via Google Forms from March to April 2025 and distributed through student groups and academic networks. The findings of the study showed that a total of 100 student responses were collected via the survey. In terms of gender, females accounted for the majority with 60% (60 students), while males represented 40% (40 students). Regarding the university year, second-year students had the highest proportion (31%), followed by third-year students (29%), final-year students (24%), and first-year students with the lowest proportion (16%). All respondents were undergraduate students from diverse academic disciplines. The sample included students from different academic years, ensuring representation across levels of study (see Table 2).

Table 2. Descriptive characteristics for participants

Characteristic		Total (*N*)	Percentage (%)
Gender	Female	60	60
	Male	40	40
University year	1st	16	16
	2nd	31	31
	3rd	29	29
	4th	24	24
How often do you use AI chatbots?	Never	0	0.0
	Rarely	0	0.0
	Occasionally	15	15
	Frequently	37	37
	Very often	48	48
How effective is using AI chatbots for yourself?	Ineffective	0	0.0
	Slightly effective	2	2
	Normal	10	10
	Effective	39	39
	Very effective	49	49

C. Analyzing of Data

After the evaluation process, the total number of valid responses used for analysis was 100. Firstly, based on the specified parameters, significance level α = 0.05, statistical power = 0.80, and effect size f^2 = 0.15, and according to the research model (Fig. 1), the maximum number of independent variables pointing to one dependent variable was two, which was consistent with the calculation from G*power [48]. Secondly, the sample size also met the minimum standard recommended by [49, 50]. The survey data were analyzed using SmartPLS 4.0 software.

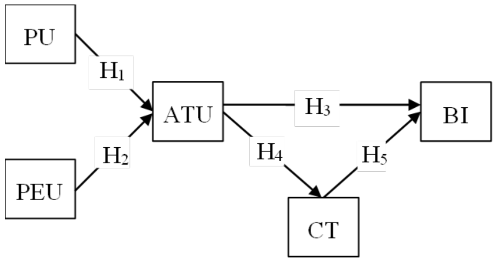

Fig. 1. Research model.

In addition to the canonical TAM specification, we tested an alternative operationalization in which PU and PEU were modeled as a single Perceived Usefulness-and-Ease (PU-E), reflecting learners' holistic appraisal of AI-chatbot utility-in-use. This alternative specification was pre-specified to examine model robustness in GenAI contexts where ease-of-use may be less differentiating. Both model specifications are reported to allow transparent comparison and to reduce the risk of capitalizing on chance.

Before running the analysis, the dataset was checked for missing values and outliers. Data were analyzed using PLS-SEM with SmartPLS 4.0, following a two-step approach: (1) assessment of the measurement model and (2) evaluation of the structural model. Regarding the measurement model, item reliability was examined with factor loadings expected to be above 0.70 [49]. Construct reliability was evaluated drawing on Cronbach's alpha and Composite Reliability (CR), each adopting a cut-off value of 0.70 [49, 50]. Adequate convergent validity is demonstrated by AVE values greater than 0.50. The assessment of discriminant validity indicated that HTMT values were below 0.90, as supported by the Fornell-Larcker criterion [51, 52]. For the structural model, the model's explanatory power was assessed by R^2 values, effect sizes f^2, and predictive relevance Q^2 (> 0). Finally, bootstrapping was implemented to examine the statistical significance of the structural paths ($t > 1.96$, $p < 0.05$) [50].

IV. Result

A. Measurement Model Assessment

The measurement model demonstrated adequate indicator reliability, as all factor loadings exceeded the recommended threshold of 0.70, ranging from 0.840 to 0.914 (Table 3) [50]. The Cronbach's alpha values ranged from 0.795 to 0.889, rho_A values from 0.796 to 0.892, and composite reliability (CR) values from 0.897 to 0.931, all exceeding the recommended minimum of 0.70 (Table 3), indicating satisfactory internal consistency reliability across the constructs. Convergent validity was supported, as the Average Variance Extracted (AVE) values ranged from 0.744 to 0.830, exceeding the recommended cut-off value of 0.50 [50]. Collinearity was assessed using Variance Inflation Factors (VIF), with all values ranging from 1.771 to 2.930, and remaining below the conservative threshold of 3.3 [50], indicating that multicollinearity was not a concern in the measurement model.

Table 3. Reliability and convergent validity indices of the first measurement model

Components	Factor loading	VIF	Cronbach's Alpha	rho_A	CR	AVE
ATU1	0.873	2.033				
ATU2	0.872	2.121	0.858	0.859	0.913	0.778
ATU3	0.902	2.391				
BI1	0.840	1.814				
BI2	0.854	1.835	0.828	0.834	0.897	0.744
BI3	0.893	2.108				
CT1	0.908	2.930				
CT2	0.913	2.810	0.889	0.892	0.931	0.818
CT3	0.891	2.247				
PEU1	0.872	2.165				
PEU2	0.870	2.196	0.854	0.875	0.911	0.773
PEU3	0.895	2.011				
PU1	0.914	1.771	0.795	0.796	0.907	0.830
PU2	0.908	1.771				

Next, the square root of the AVE (on the diagonal) was confirmed to be greater than all correlation coefficients with other variables in the same row, indicating adequate discriminant validity [51]. Regarding HTMT, most construct pairs exhibited values below the recommended threshold of 0.90 [53]. However, the HTMT value between CT and BI was relatively high (HTMT = 0.890), approaching the threshold. Given the conceptual proximity between reflective critical engagement and intention-related behaviors, this result was considered theoretically plausible. Item wording was therefore reviewed to ensure conceptual distinctiveness between these constructs. In addition, the HTMT value between PU and PEU exceeded the recommended threshold (HTMT = 1.045), indicating insufficient discriminant validity between these two constructs. This result suggests that, in the context of AI chatbots, students may perceive PU and PEU as highly intertwined. Based on this empirical evidence, PU and PEU were subsequently integrated into a single construct PU-E in the revised measurement model, as reported in Table 4. This adjustment resolved the discriminant validity concern and may suggest context-specific overlap between these constructs within the AI chatbot setting.

Table 4. Fornell–Larcker and HTMT indices for the discriminant validity of the measurement scale

First Measurement Model	Revised Measurement Model
Fornell-Larcker Criterion	
ATU 0.882	ATU 0.882
BI 0.488 0.863	BI 0.488 0.863
CT 0.374 0.771 0.904	CT 0.374 0.771 0.904
PEU 0.588 0.473 0.407 0.879	PU-E 0.575 0.468 0.388 0.862
PU 0.502 0.418 0.324 0.861 0.911	
Heterotrait-Monotrait Ratio (HTMT)	
ATU	ATU
BI 0.581	BI 0.581
CT 0.427 0.890	CT 0.427 0.890
PEU 0.673 0.553 0.459	PU-E 0.637 0.531 0.423
PU 0.604 0.516 0.382 *1.045*	

Overall, the measurement model demonstrates satisfactory reliability and validity. Identified discriminant validity concerns were addressed through theoretically grounded interpretation and alternative model specification, supporting the robustness of the measurement framework employed in this study.

B. Structural Model Assessment

The hypotheses of the model were tested using the bootstrapping method [50, 54]. In the initial structural model (Table 5), ATU was significantly associated with BI (β = 0.232, t = 2.824, p = 0.005, f^2 = 0.129) and CT (β = 0.374, t = 3.298, p = 0.001, f^2 = 0.162). These effect sizes indicate that ATU has a moderate influence on both BI and CT. The CT showed a strong association with BI (β = 0.684, t = 8.494, p < 0.001), with a large effect size (f^2 = 1.118), indicating substantial explanatory power within the model. This result suggests that CT plays a more prominent role compared to ATU in shaping BI. The PEU was significantly associated with ATU (β = 0.604, t = 4.127, p < 0.001), whereas PU was not (β = −0.018, t = 0.162, p = 0.872). The non-significant effect of PU indicates that its contribution to ATU was not supported in this model.

Specific indirect effects (Table 6) were observed through ATU and CT, while indirect pathways involving PU were not supported. These results indicate that ATU and CT sequentially mediate the relationship between system perceptions and BI, highlighting the importance of both attitudinal and cognitive mechanisms in shaping students' intention to use AI chatbots. This suggests that PU does not play a meaningful mediating role in influencing BI in this context. Given the nonsignificant role of PU and the lack of discriminant validity between PU and PEU identified in the measurement model, a revised structural model was estimated by integrating PU and PEU into a single construct PU-E. As reported in Table 5, PU-E was strongly associated with ATU (β = 0.575, t = 5.176, p < 0.001, f^2 = 0.493). The associations among ATU, CT, and BI remained stable in both magnitude and significance, with CT continuing to exhibit a strong association with BI (β = 0.684, t = 8.641, p < 0.001).

Regarding explanatory power (Table 7), the revised model accounted for a substantial proportion of variance in BI (R^2 = 0.633), while ATU showed moderate explained variance, whereas CT showed a low level of explained variance (R^2 = 0.131). All Q^2 values were positive, thereby confirming the model's predictive relevance. Overall, the structural model results indicate that ATU and CT constructs are strongly associated with students' self-reported BI to use AI chatbots within the extended TAM framework. Given the cross-sectional design, these findings should be interpreted as predictive relationships rather than causal effects. The structural relationships for the initial and revised models are illustrated in Fig. 2 and Fig. 3, respectively.

Table 5. Path coefficients of the first measurement model

Effects Type	Hypothesis	β	SD	*T*-Statistics	*P*-values	f^2	Result
Direct Effects	ATU → BI	0.232	0.083	2.785	0.005	0.129	Supported
	ATU → CT	0.374	0.113	3.298	0.001	0.162	Supported
	CT → BI	0.684	0.080	8.494	0.000	1.118	Supported
	PEU → ATU	0.604	0.146	4.127	0.000	0.145	Supported
	PU → ATU	−0.018	0.112	0.162	0.872	0.000	*Unsupported*
Specific Indirect Effects	PEU → ATU → BI	0.140	0.062	2.280	0.023		Supported
	PU → ATU → BI	−0.004	0.027	0.155	*0.877*		*Unsupported*
	PEU → ATU → CT → BI	0.154	0.077	2.007	0.045		Supported
	ATU → CT → BI	0.255	0.090	2.825	0.005		Supported
	PU → ATU → CT → BI	−0.005	0.033	0.142	*0.887*		*Unsupported*
	PEU → ATU → CT	0.226	0.106	2.124	0.034		Supported
	PU → ATU → CT	−0.007	0.046	0.147	*0.883*		*Unsupported*

Table 6. Path coefficients of the revised measurement model

Effects Type	Hypothesis	β	SD	*T*-Statistics	*P*-values	f^2	Result
Direct Effects	ATU → BI	0.232	0.082	2.824	0.005	0.129	Supported
	ATU → CT	0.374	0.115	3.260	0.001	0.162	Supported
	CT → BI	0.684	0.079	8.641	0.000	1.118	Supported
	PU-E → ATU	0.575	0.111	5.176	0.000	0.493	Supported
Specific Indirect Effects	PU-E → ATU → BI	0.134	0.051	2.615	0.009		Supported
	ATU → CT → BI	0.255	0.091	2.822	0.005		Supported
	PU-E → ATU → CT → BI	0.147	0.074	1.990	0.047		Supported
	PU-E → ATU → CT	0.215	0.100	2.155	0.031		Supported

Table 7. Coefficient of determination and predictive relevance of the structural models

Variable	R^2 Adjusted		Q^2	
	First Model	Revised Model	First Model	Revised Model
ATU	0.333	0.323	0.266	0.254
BI	0.633	0.633	0.443	0.443
CT	0.131	0.131	0.096	0.096

V. Discussion

This study advances understanding of students' use of conversational AI in higher education by extending the TAM with CT as a cognitive construct. The empirical results suggest that the extended model demonstrates substantial explanatory capacity for Vietnamese university students' self-reported intention to use chatbots for learning purposes, accounting for 63.3% of the variance in BI (R^2 = 0.633). This level of explained variance is comparable to, and in some cases higher than, that reported in prior research examining technology acceptance in educational contexts [21]. Compared with prior TAM-based studies focusing on self-efficacy or trust [27], the present study highlights CT as a complementary cognitive construct associated with more reflective and deliberate intentions to use AI chatbots.

A central finding concerns the association between CT and students' intention to use chatbots. In contrast to findings suggesting that AI literacy alone may not directly translate into intention [55], the present results indicate that CT is significantly associated with students' intention to use AI chatbots, reflecting users' active evaluation and critical assessment of AI-generated outputs. Among all predictors in the model, CT exhibited the largest standardized path coefficient ($\beta = 0.684$) and a very large effect size ($f^2 = 1.118$), indicating a substantial contribution to explaining variance in BI. This finding is noteworthy, as it contrasts with traditional TAM assumptions in which perceptual factors such as PU and PEU are typically the dominant predictors of BI [18, 21]. This may indicate that in AI-mediated learning environments, cognitive engagement plays a more central role than instrumental evaluations. While this result aligns with prior studies emphasizing the role of CT [16, 17, 32], it extends this line of research by demonstrating that CT functions not merely as an outcome, but as a direct predictor of BI in AI contexts. As interaction with chatbots requires analysis, evaluation, and reflective judgment [13, 41], CT appears to play a central role in supporting students' active and reflective engagement in this context. This suggests that CT may function not only as a cognitive skill but also as a key mechanism that reshapes how traditional TAM constructs operate in interactive AI contexts. While earlier work has often conceptualized CT as an outcome of learning activities or as indirectly linked to technology use through engagement or perceived value [19], the present findings indicate that CT is closely associated with students' intentions to engage with chatbots within the proposed model.

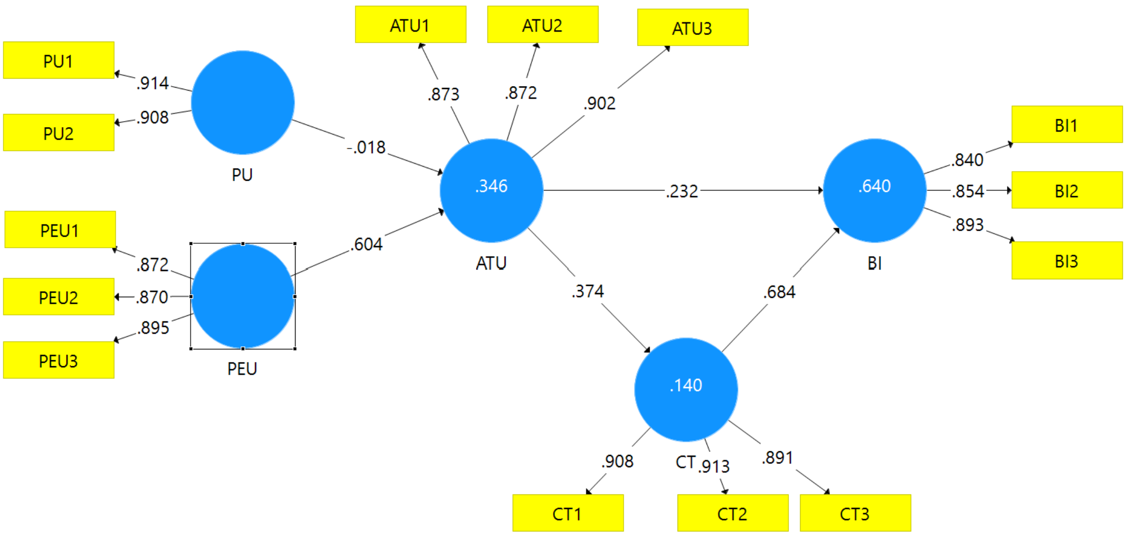

Fig. 2. First measurement model.

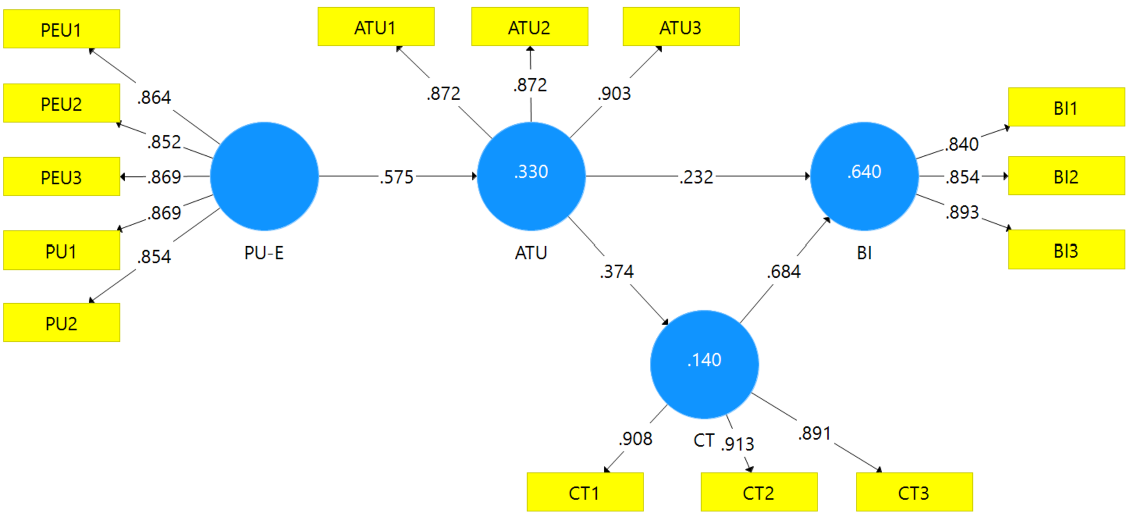

Fig. 3. Revised measurement model.

This pattern may be understood by considering the cognitive demands inherent in interacting with conversational systems. Effective use of chatbots for learning requires learners to formulate appropriate queries, evaluate system outputs, verify information accuracy, and determine the relevance of responses to academic tasks. These activities correspond closely to core dimensions of CT, including analysis, evaluation, and reflective judgment [13, 14, 41]. From this perspective, CT may be interpreted as a cognitive condition that may facilitate students' engagement with chatbots in a purposeful and reflective manner [11, 35].

A significant linkage between CT and BI was observed in this study. This finding aligns with prior Vietnamese research highlighting concerns about diminished critical engagement when AI tools are used unreflectively [10]. This finding further supports evidence suggesting that effective engagement with AI chatbots depends on users' cognitive capacities, particularly their ability to evaluate and regulate system outputs, which reduces the likelihood of uncritical reliance on GenAI [33]. A similar mechanism is suggested in classroom-based intervention research, where students used GenAI not merely to retrieve information but as cognitive support for understanding and explanation-building, with teachers guiding students to critically evaluate AI-generated explanations. In Ratniyom *et al.* [56] this structured use of Microsoft Copilot was associated with significant gains in explanation competency, reinforcing the importance of guided evaluation rather than uncritical acceptance of AI outputs. In this regard, CT may function as a cognitive condition that may support more reflective and responsible use, complementing perceptual evaluations related to usefulness and ease of use. Similar observations have been reported in recent studies highlighting that students who actively question and evaluate information provided by conversational systems tend to demonstrate deeper engagement and more responsible patterns of use [32, 40].

The findings also refine the understanding of PU and PEU in the context of conversational AI. As shown in Fig. 2, the initial modelindicates that PU did not show a significant association with ATU when treated as a separate construct. As illustrated in Fig. 3, the resived model demonstrates that when PU and PEU were integrated into a single combined perception, this PU-E construct exhibited a strong and significant association with attitude. This result suggests that, for university students, perceptions of usefulness may be closely intertwined with the ease and fluency of interaction when engaging with chatbots. The lack of discriminant validity between PU and PEU may reflect either a measurement limitation or a substantive psychological phenomenon, and thus should be interpreted with caution. Consistent with this interpretation, prior research indicates that users' evaluations of GenAI often emerge from holistic interaction experiences, making it difficult to disentangle usefulness from ease of interaction in empirical models [6]. The lack of a significant direct association between PU and ATU in the present study aligns with recent findings showing that usefulness does not necessarily function as a dominant predictor when students' evaluations are shaped primarily by experiential aspects of system use [20]. Rather than assessing usefulness as a distinct instrumental benefit, students may form judgments based on their overall interaction experience, including responsiveness and conversational flow [26, 28]. This suggests that, in GenAI contexts, traditional TAM constructs may become cognitively integrated due to the conversational and interactive nature of the technology. Collectively, these findings converge with emerging experiential perspectives on technology use [3, 57], further research is needed to examine whether such integrated perceptions are characteristic of conversational technologies more broadly or specific to particular educational contexts. Another important observation is that ATU remained significantly associated with both BI and CT. This finding indicates that affective evaluations continue to play a meaningful role even when cognitive factors are incorporated into the model. Rather than displacing attitude, CT appears to complement it by shaping how students evaluate, regulate, and reflect on their interactions with chatbots. This combination of affective and cognitive pathways is consistent with earlier research suggesting that technology use in education is influenced by both emotional responses and higher-order cognitive processes [18, 21, 58].

The results are particularly relevant in the Vietnamese higher education context. Prior studies have reported that Vietnamese students' CT skills remain at a moderate level, shaped by cultural norms, instructional practices, and limited opportunities for open academic debate [42, 43]. Concurrently, awareness and use of conversational AI among university students in Vietnam have increased rapidly [5]. The strong association between CT and intention to use chatbots observed in this study suggests that such technologies may provide opportunities that are consistent with the activation and practice of CT when embedded within pedagogically meaningful learning activities. Universities should integrate AI chatbots into learning environments in ways that promote critical engagement, such as embedding reflective and evaluative tasks. Educators should guide students to actively question, verify, and iteratively interact with AI-generated content, rather than using chatbots passively. This interpretation aligns with both national and international research emphasizing the need to align digital technologies with instructional approaches that promote questioning, evaluation, and reflective learning [35, 46]. Recent national policy initiatives in Vietnam, including strategies on AI and emerging frameworks for digital competence, provide a timely foundation for aligning chatbot use with broader educational goals [59–61].

VI. Conclusion

This study examined university students' BI to use AI chatbots in educational contexts by extending the TAM with CT in the Vietnamese university context. The findings demonstrate that the proposed model provides substantial explanatory power, with CT emerging as the most salient factor associated with students' use of AI chatbots. In addition, ATU remained significantly associated with both BI and CT, indicating the continued relevance of affective evaluations alongside cognitive engagement. While PU did not show a significant association with ATU when modeled independently, integrating PU and PEU into a single construct, PU-E, resulted in stronger and more coherent relationships, suggesting that students evaluate AI chatbots based on their overall interaction experience.

Theoretically, this study contributes to the literature by extending TAM by incorporating CT as a higher-order cognitive construct in the context of generative AI. Practically, the findings highlight the importance of designing AI-supported learning environments that actively foster students' CT through structured activities such as prompting, verification, and reflective evaluation of AI-generated content.

Despite these contributions, several limitations should be acknowledged. First, the sample was drawn from a single institutional context, which may limit generalizability. Second, the cross-sectional design restricts causal inference. Third, the model explains a relatively modest proportion of variance in CT, suggesting that additional antecedents (e.g., trust, perceived risk, and learning motivation) may be relevant. Future research should employ longitudinal or experimental designs and include more diverse samples to further validate and extend these findings. Overall, the findings underscore the importance of integrating higher-order cognitive dimensions into models of technology acceptance in the era of generative AI.

DECLARATION

All participants provided informed consent by proceeding after reading a statement on the study's purpose, anonymity, and voluntary nature of participation.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

M.-D. T. N. conducted the data analysis and drafted the initial manuscript; D.-N. L. developed the methodology, validated the results, contributed to the original draft, performed manuscript revision, and supervised the study. All authors have read and approved the final manuscript.

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