A Hybrid ECM–KM Model for Predicting Sustainable Use of AI-based Chatbots in Higher Education

Ngoc-Hong Duong *, Hong Anh Vo Thi, Kim Hue Phan Thi, and Truc Quynh Tran Thi

School of International Business and Marketing, University of Economics Ho Chi Minh City, Ho Chi Minh City, Vietnam
Email: hongdn@ueh.edu.vn (N.-H.D.); anhvo.31231026739@st.ueh.edu.vn (H.A.V.T.); huephan.31231023855@st.ueh.edu.vn (K.H.P.T.); quynhtran.31231026498@st.ueh.edu.vn (T.Q.T.T.)
*Corresponding author

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***Abstract*—This study explores the sustainable use of Artificial Intelligence (AI) chatbots in Higher Education by integrating the Expectation Confirmation Model (ECM) with Knowledge Management (KM) factors. Although the research and application of chatbots in universities have expanded to support both learning and administrative processes, there remains a lack of comprehensive strategies to encourage their continued practical use, particularly in developing countries such as Vietnam. A conceptual model was developed by incorporating ECM and KM constructs to investigate their influence on students' behavioral intentions and the long-term sustainability of chatbot usage. Data were collected from 468 Vietnamese university students and analyzed through Structural Equation Modeling (SEM). The results demonstrate the importance of aligning user expectations with chatbot performance and of encouraging active participation in knowledge-sharing and management activities to ensure the long-term sustainability of this technology. This study provides theoretical contributions and managerial implications for educational institutions looking to adopt AI-based solutions to enhance student learning experiences and promote digital transformation effectively and sustainably.**

***Keywords*—Artificial Intelligence (AI)-based chatbots, behavioral intention, expectation confirmation model, Higher education, knowledge sharing, sustainable use of technology**

I. Introduction

Chatbots are advanced technological tools that have gained widespread recognition for their intelligent communication and interaction capabilities, enhancing the quality of teaching and learning in higher education [1]. This technology provides flexible and personalized learning experiences that address the diverse needs of specific target groups. Owing to their effective integration of technological innovation, social responsibility, and sustainable development orientation, chatbots are regarded as a modern and long-term solution in the education sector [2, 3]. Higher education institutions can leverage advances in chatbots and artificial intelligence to continuously improve the effectiveness of teaching, learning, and research, while simultaneously reducing the high costs of building, operating, and maintaining complex information technology infrastructure. In practice, many universities worldwide have already implemented chatbots and Artificial Intelligence (AI)-based systems to support both academic and administrative activities [4]. The adoption of these digital solutions significantly enhances user satisfaction by automating processes, improving staff work efficiency, and providing continuous 24/7 support for learners [3, 5].

Strong support for this widespread adoption is reflected in a substantial body of scientific research on chatbots. These studies have shown steady growth since 2003. As of August 2021, the Web of Science database recorded 813 publications containing keywords such as "chatbot" or "chatbots" in titles during the period from 2003 to 2021. Several authors have also found that students' initial experiences with chatbots are generally positive, particularly regarding rapid, convenient access to information. However, they also report that when chatbots begin to provide inaccurate, irrelevant, or poorly aligned information, users' trust declines significantly. Therefore, the development of a comprehensive, regularly updated, and systematically organized knowledge base is essential [1].

Although numerous studies have acknowledged the positive role of AI-based chatbots in enhancing student satisfaction, engagement, and continuance intention in higher education [6, 7], the existing scientific evidence remains fragmented and lacks a systematic perspective. Most prior studies have examined isolated aspects of chatbots, such as perceived ease of use, perceived benefits, or user experience, rather than comprehensively addressing the post-adoption process and the sustainable use of this technology. Consequently, a comprehensive and rigorous theoretical framework that explains the core factors governing the adoption, use, and sustained use of AI-based chatbots in higher education has yet to be fully established [8]. In Vietnam, although several studies have investigated the application of AI in higher education, they have primarily focused on initial technology acceptance or on teaching effectiveness. In contrast, the sustainable use of AI-based chatbots from an integrated post-adoption and knowledge management perspective remains underexplored. Meanwhile, most theoretical frameworks and analytical models related to AI-based chatbots have been developed in international contexts and have not sufficiently captured the specific characteristics of Vietnam's higher education system.

In light of this practical context, this study aims to address the aforementioned theoretical gap by developing and empirically validating an integrated research model. Specifically, the proposed model is built on a combination of the core constructs of the Expectation-Confirmation Model (ECM), including expectation confirmation, perceived usefulness, and satisfaction, together with key factors from Knowledge Management (KM), namely knowledge sharing, knowledge absorption, and knowledge application. This integrative approach enables a simultaneous examination of learners' cognitive-behavioral aspects and the processes of knowledge processing and utilization during interactions with AI-based chatbots. The objective of the study is to identify the key determinants influencing the

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effective use of AI chatbots in students' learning activities, thereby elucidating the mechanisms that drive both the adoption and continued use of this technology. While prior studies, such as [1], have examined the role of knowledge management factors in chatbot sustainability, this study extends the existing literature by explicitly incorporating Behavioral Intention as a transitional psychological mechanism linking post-adoption evaluations and sustainable use. Moreover, the ECM-KM framework is empirically validated within the Vietnamese higher education context, which remains underrepresented in chatbot adoption research. The primary research subjects are students enrolled in universities and colleges in Vietnam, within the context of higher education being powerfully shaped by digital transformation and the pursuit of sustainable development.

This study makes three key contributions. First, it extends the Expectation-Confirmation Model by integrating Knowledge Management mechanisms to explain sustainable use of chatbots in higher education. Second, it empirically validates the proposed ECM–KM framework using data from university students, highlighting the distinct roles of post-adoption evaluations and knowledge processes. Third, it provides evidence-based implications for universities and policymakers on how to design and govern AI chatbots to support long-term learning sustainability.

The format of this study is as follows: The Theoretical Foundation Section underscores the importance of ECM and KM factors in developing educational chatbots, providing the theoretical underpinning for Hypothesis Development. The Methodology Section details the steps involved, from hypothesis development to data collection. The analysis's conclusions are presented in Section Results. The Conclusion section presents the theoretical contributions and Managerial Implications.

II. Literature Review

A. Chatbot

A chatbot is an artificial intelligence program designed to simulate Human-Computer Interaction (HCI) [9]. This is computer software designed to simulate conversations with users over the Internet [10]. Chatbots can communicate with users or other chatbots in human language by using sentiment analysis and Natural Language Processing (NLP) [11]. The rapid development of AI technology has driven the widespread adoption of NLP-based chatbots across various application domains [12]. Chatbot technology, such as virtual assistants, has significantly streamlined and enhanced the learning process by integrating advanced pedagogical methods and technologies [13]. This study examines how students utilize AI-based chatbots sustainably in learning by incorporating a model that extracts structures from elements of ECM and KM. It is crucial to assess the extent to which this technology is used effectively in classrooms. This will aid in forecasting how pupils will feel about this new technology [14, 15]. Thus far, interest in AI has grown dramatically as chatbots have progressively gained popularity [13]. AI-based chatbot activities have particular potential to improve teaching and learning in the classroom [2]. Recent studies continue to demonstrate that AI-powered chatbots can enhance student engagement, motivation, and learning outcomes by providing instant feedback and personalized learning support [7, 16]. Furthermore, systematic reviews indicate that chatbots play a significant role in supporting self-regulated learning and continuous knowledge acquisition in higher education settings [17].

B. Expectancy Confirmation Model (ECM)

Model: The Technology Acceptance Model (TAM) has been combined with Expectancy-Confirmation Theory (ECT) to develop a new model, the Expectancy-Confirmation Model (ECM) [18]. Through key constructs such as Expectation Confirmation, Perceived Usefulness, and Satisfaction, ECM aims to explain consumers' behavioral intentions following the initial acceptance phase and the factors that influence their continued use intentions [8]. Currently, ECM remains a popular model for evaluating consumer satisfaction with internet-based technologies [6]. According to a recent study on chatbots, users found the technological aspects of chatbots appropriate for their work needs, and that their expectations were also met [19]. This supports ECM's theory that consumers are more likely to stick with a technology if it meets their expectations. However, ECM primarily focuses on users' cognitive and emotional evaluations after use, without clarifying how intelligent technologies, such as AI-based chatbots, continuously support learning and knowledge processing in educational contexts. Therefore, to provide a more comprehensive explanation of sustainable chatbot usage, it is necessary to broaden the perspective beyond mere post-use evaluations and consider the functional role of chatbots in supporting knowledge-related activities.

C. Knowledge Management (KM)

Knowledge Management (KM) has been comprehensively defined as an evolving set of organizational design principles, operational processes, structures, tools, and technologies that effectively harness the creative power of knowledge [20]. Knowledge management plays an intermediary role in artificial intelligence and decision support systems. Some studies have incorporated KM factors into theoretical models rather than simply measuring organizational-level adoption [21, 22]. This led to the conclusion that if students perceive chatbots as a helpful tool for learning, sharing, and applying knowledge, they will continue to use them. Additionally, recent literature has begun to expand and develop at an individual level, specifically applied to this study [23, 24]. From a theoretical integration perspective, while ECM captures how students evaluate chatbots based on Expectation Confirmation, Perceived Usefulness, and Satisfaction, KM reflects the functional learning mechanisms through which chatbots support academic knowledge processes. The integration of ECM and KM enables this study to conceptualize the sustainable use of chatbots as a dual, interactive process that shapes students' behavioral intentions and long-term use. This integration provides a more comprehensive theoretical framework for explaining the adoption of sustainable chatbots in higher education environments.

D. Expectation Confirmation

According to Expectation-Confirmation Theory, when users' initial expectations are confirmed through actual system performance, they experience positive affective responses that manifest as satisfaction. Expectancy validation can be understood as the degree of alignment between the user's initial expectations and the system's actual behavior [8]. If they believed learners were using the learning system as expected or better, they would perceive it as valuable and even indispensable for learning [6, 25]. The positive impact of EC on usefulness has been demonstrated in empirical studies across contexts such as online banking [26], social media sites [27], and e-learning [28]. Specifically, in the area of innovative learning tools, when students' expectations are met or exceeded, they perceive chatbots as efficient learning tools [29]. When chatbots provide timely, personalized, and accurate assistance, they become learning companions. Satisfaction occurs when system performance meets or exceeds users' pre-usage expectations, resulting in a sense of fulfillment and a positive experience [8]. Based on this, we formulate the following hypothesis:

H1: Expectation confirmation positively influences perceived usefulness.

H2: Expectation confirmation is positively related to satisfaction.

E. Perceived Usefulness

Usefulness is "the degree to which a person believes that using a particular system will improve their performance" [30]. Perceived usefulness is strongly associated with satisfaction in the following scenarios applied in previous studies [26, 28], and perceived usefulness is considered a major predictor of satisfaction [31]. For example, when a tool helps increase student learning effectiveness in a way such as by using chatbots [32], improving communication [2], or providing synchronous support while learning [33], students are more likely to report satisfaction when the tool delivers tangible benefits. Previous studies have consistently identified perceived usefulness as the primary motivator for users' intention to continue using the technology [34, 35]. However, the negligible correlation between perceived usefulness and satisfaction suggests that mere instrumental value is insufficient to elicit positive emotions when using AI-based chatbots. While students may perceive chatbots as useful for retrieving information or completing tasks, satisfaction in an educational context is also strongly influenced by the quality of interaction, the naturalness of the conversation, responsiveness, and perceived empathy. In fact, chatbots can effectively support everyday learning tasks but fail to meet student expectations in more complex, context-dependent learning situations, resulting in a "useful but frustrating" experience. This finding is consistent with emerging studies showing that satisfaction with AI systems depends not only on functional performance but also on social presence and interaction richness, particularly in learning environments. Students' perceptions of chatbots as practical tools to support and enhance learning performance significantly influence their perceptions of the tool's usefulness after deployment [7]. Based on this, we hypothesize:

H3: Perceived usefulness positively influences satisfaction.

H4: Perceived usefulness positively influences behavioral intention.

H5: Satisfaction is positively related to Behavioral Intention.

F. Knowledge Sharing

One of the critical elements in facilitating collaborative learning and educational novelty is knowledge sharing. It is the spread of a variety of resources among people with a common goal [36]. This mechanism facilitates knowledge exchange, induces knowledge creation, and enhances the learning experience and relationships within the academic community [37–39]. When chatbots are perceived as helpful for exchanging information, ideas, and academic knowledge within the learning community, the adoption and integration of chatbots into educational practices are highly likely to be driven by learners' intention to use [26, 36, 40]. Based on this understanding, the following hypothesis is proposed:

H6: Knowledge sharing positively influences behavioral intention.

G. Knowledge Acquisition

Referred to as "the construction that applies current data and discovers new knowledge" [41], TEL is a fundamental constituent in knowledge management and academic progress [40, 42]. The extent to which information systems can facilitate this process is widely recognized as a significant factor influencing user acceptance [21, 43]. Intelligent learning tools, such as chatbots, significantly enhance this capability by providing individualized support, improving content retention, and enabling immediate access to relevant information [44]. They also enable students to navigate their teaching materials, locate prior discussions, and consult external resources, such as library databases, thereby reducing the complexity of knowledge management [45]. Based on this, we propose:

H7: Knowledge acquisition positively influences Behavioral Intention.

H. Knowledge Application

Knowledge application is defined as "a process that allows users to seamlessly access knowledge techniques by efficiently storing and retrieving them" [24]. In education, the extent to which a platform encourages learners to apply the knowledge they have acquired is an indicator of their willingness to use that platform long-term [36]. Innovative tools like chatbots provide instant access to collected solutions and offer direct guidance. With this functionality, chatbots are effective at assisting learners in applying learned concepts to classroom activities and assignments. However, the application of knowledge to behavioral intent may reflect the limitations of AI-based chatbots in supporting higher-order learning and knowledge transfer, with negligible effectiveness. Although chatbots can assist students in understanding concepts and accessing information, applying knowledge to practical exercises often requires contextual judgment, problem-solving skills, and instructor guidance. This demonstrates that students may recognize the informational value of chatbots but do not consider them sufficiently reliable or effective to apply knowledge independently. However, from a behavioral perspective, when learners perceive chatbots as effectively supporting the application of learned knowledge to learning tasks, this functional value may enhance their willingness to continue using the system. Accordingly, the application of knowledge is expected to positively affect students' behavioral intentions toward long-term chatbot use. Based on this understanding, we propose the following hypothesis:

H8: Knowledge application positively influences Behavioral Intention.

I. Behavior Intention

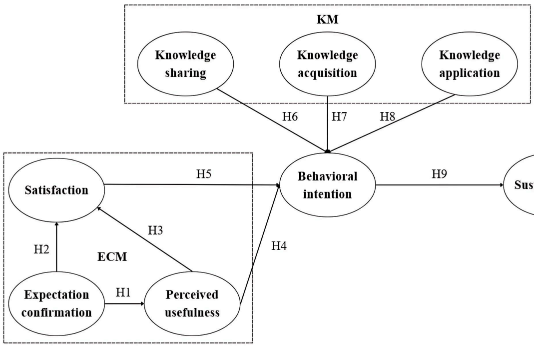

Fig. 1. Theoretical model.

Behavioral intention is an individual's willingness or plan to perform an activity and plays a crucial role in the viability and long-term sustainability of technology systems. Although [1] consider sustainable use a direct result of knowledge management factors, the current research explicitly incorporates Behavioral Intention as a key psychological mechanism linking post-adoption evaluations to long-term use behavior. Based on post-adoption and continuation theories (e.g., ECM, TAM, and UTAUT), behavioral intention denotes a user's conscious willingness to continue using the technology. It is widely recognized as a strong antecedent of actual and sustained use. By positioning Behavioral Intention as an intermediary construct between satisfaction, knowledge-related factors, and sustainable use, this study extends previous ECM–KM frameworks by capturing the motivational shift from evaluation to long-term behavioral commitment. In educational settings, students' intention to use digital tools, such as e-learning systems and chatbots, is crucial for encouraging sustainable use, a key step in shaping students' attitudes toward these technologies [36]. In this study, sustainable use is conceptualized as a long-term behavioral outcome, reflecting users' continued voluntary, regular use of AI-based chatbots over time. Unlike Behavioral Intention, which captures the user's motivational readiness, sustainable use represents actual persistence in using the chatbot after initial adoption. Accordingly, sustainable use is modeled as an outcome variable, driven by behavioral intentions and post-adoption evaluations, rather than a mediating variable within the ECM–KM framework. Because intrinsic motivation drives users, their continued use contributes to the long-term success and sustainability of the systems they use. Based on this reasoning, we propose the following hypothesis:

H9: Behavioral Intention is positively related to sustainability.

The theoretical hypothesis model for the above-discussed literature is illustrated in Fig. 1.

III. Methodology

This study used quantitative research methods to evaluate the factors influencing the long-term adoption of AI-powered chatbots in higher education. A conceptual framework was developed by integrating the Exception Confirmation Model (ECM) with key dimensions of Knowledge Management (KM) to examine how factors influence behavioral intention and long-term chatbot use. Data were collected from 468 undergraduate students enrolled in Vietnamese higher education institutions, using an online questionnaire with a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). The survey's empirical focus was limited to learning-related chatbot use rather than administrative or institutional services. The measurement instrument was adapted from validated scales used in prior studies on AI-based chatbots, with minor wording refinements to ensure contextual appropriateness for Vietnamese higher-education students. To ensure linguistic accuracy and content validity, the questionnaire underwent back translation and was reviewed for clarity and relevance before data collection [46]. Given the country- and context-specific nature of the sample, the methodological design reflects students' post-adoption experiences with AI-based chatbots within the Vietnamese higher education context, and the findings should be interpreted accordingly. Structural Equation Modeling (SEM) was used to test the proposed hypotheses and assess relationships among latent variables. The measurement items used in this study are presented in Table 1.

Table 1. Measurement items

Construct		Measurement
Knowledge Acquisition (KA)	KA1	A chatbot application facilitates knowledge acquisition from the course material.
	KA2	A chatbot application facilitates knowledge acquisition through discussions.
	KA3	A chatbot application enables me to generate new knowledge from my existing knowledge.
	KA4	A chatbot application enables me to acquire knowledge through various resources.
	KA5	The chatbot application helps me acquire knowledge that suits my needs.
Knowledge Sharing (KS)	KS1	A chatbot application allows me to share knowledge with my instructors and classmates.
	KS2	Chatbot application supports various types of discussions.
	KS3	A chatbot application facilitates knowledge sharing in anytime, anywhere settings.
	KS4	The chatbot application enables me to share various resources with my instructors and classmates.
	KS5	Chatbot application facilitates the collaborative learning process.
Knowledge Application (KAP)	KAP1	The chatbot application provides me with instant access to various types of knowledge.
	KAP2	The chatbot application enables me to apply the knowledge I gain from the learning activities and assignments.
	KAP3	A chatbot application allows me to integrate different types of knowledge.
	KAP4	A chatbot application can help us better manage the course materials within the university.
Perceived Usefulness (PU)	PU1	The chatbot's performance benefits me.
	PU2	The advantages of chatbots outweigh the disadvantages.
	PU3	Overall, the chatbot's functions are helpful.

Construct		Measurement
Expectation Confirmation (EC)	EC1	My experience with using chatbots was better than what I expected.
	EC2	The chatbot's service level exceeded my expectations.
	EC3	The benefits of using a chatbot were better than we expected.
	EC4	Overall, most of my expectations regarding the use of a chatbot were confirmed.
Satisfaction (STS)	STS1	My experience using a chatbot was highly satisfactory.
	STS2	My experience: The chatbot was very pleasant.
	STS3	My experience with chatbots was very positive.
	STS4	My experience of using a chatbot was very delightful.
Sustainability (SUST)	SUST1	I intend to continue using the chatbot rather than discontinue its use.
	SUST2	I plan to continue using chatbots.
	SUST3	If I could, I would like to continue using chatbots.
Behavioral Intention (BI)	BI1	I will use a chatbot to solve problems related to my academic query.
	BI2	I plan to use the chatbot frequently.
	BI3	I recommend that others use a chatbot for academic matters.

IV. Results and Discussion

This section presents and discusses the study's empirical findings. First, the measurement model is evaluated for reliability and validity to assess the adequacy of the constructs. Next, the structural model is examined to test the proposed hypotheses and to assess its explanatory power. Finally, the results are discussed in light of prior studies, highlighting key theoretical insights and practical implications.

A. Descriptive Statistics

Table 2 presents the demographic characteristics of the study sample, comprising 468 participants, all of whom provided informed consent, providing an initial basis for understanding the context of AI chatbot deployment in higher education and their potential for sustainable application. Regarding gender, the majority of participants were female (61.1%), reflecting the increasing role of women in accessing and evaluating current digital learning tools. The dominant age group was 20–25 (55.1%), followed by those under 20 (24.6%) and over 25 (20.3%). This reflects that the majority of participants were students enrolled in formal education programs, a stage considered technologically proficient and with high.

Table 2. Sample characteristics

Characteristics		Frequency	Percent	Valid Percent	Cumulative Percent
Gender	Male	182	38.9	38.9	38.9
	Female	286	61.1	61.1	100.0
	Total	468	100.0	100.0	
Age	Under 20 years old	115	24.6	24.6	24.6
	20-25 years old	258	55.1	55.1	79.7
	Over 25 years old	95	20.3	20.3	100.0
	Total	468	100.0	100.0	
Academic standing	Year 1	66	14.1	14.1	14.1
	Year 2	194	41.5	41.5	55.6
	Year 3	83	17.7	17.7	73.3
	Master degree	125	26.7	26.7	100.0
	Total	468	100.0	100.0	
Academic Disciplines	Information Technology	86	18.4	18.4	18.4
	Business Administration	146	31.2	31.2	49.6
	Engineering	86	18.4	18.4	67.9
	Finance/Banking	75	16.0	16.0	84.0
	Customs/Tax/Law	75	16.0	16.0	100.0
	Total	468	100.0	100.0	

Expectations for the learning support capabilities of digital tools. By educational level, second-year students accounted for the largest proportion (41.5%), followed by working professionals (26.7%). Furthermore, the diversity of academic disciplines, particularly Business Administration (31.2%), along with IT, Engineering, Finance-Banking, and Law, indicates a fairly diverse sample across academic years. This study focuses on individuals with specific educational backgrounds and experiences and demonstrates a relatively diverse distribution across fields, thereby enhancing the representativeness and reliability of the research results.

B. Data Analysis

The scales in the research model achieve both reliability and convergent validity, according to the findings of the external load factor analysis and reliability indicators. When an observed variable's outer loading coefficient is greater than 0.7, it is deemed significant; variables with outer loading coefficients less than 0.4 will be eliminated to maintain representativeness [47]. All of the observed variables associated with the latent concepts BI, EC, KA, KAP, KS, PU, STS, and SUST had outer loading coefficients greater than 0.7, with the lowest value being 0.765, according to Table 3. This indicates that no variables are omitted from the model, and that the observed variables exhibit high correlations and accurately measure their respective latent constructs. To evaluate the scale's internal consistency, reliability indices such as Cronbach's Alpha, composite reliability (rho_c), and rho_a were also examined. Cronbach's Alpha tends to underestimate dependability, rho_c tends to overestimate, and rho_a, which typically falls between these two values, is seen to be a more accurate picture of the concept's genuine reliability. The minimum allowable value for these indices is 0.7 [48]. The results in Table 3 show that all three indicators exceed the threshold of 0.7, confirming the scale's high stability and reliability. The argument for convergent validity is further strengthened by the Average Variance Extracted (AVE) of all concepts above 0.5 [49] in conjunction with strong outer loading coefficients. As a result, the model's scales satisfy the standards for measurement validity and reliability, offering a strong basis for further structural investigations.

Table 3. Construct reliability and validity analysis results

Construct	Items	Outer Loadings	Cronbach's a	CR (rho_a)	CR (rho_c)	AVE
BI	BI1	0.908	0.874	0.877	0.923	0.799
	BI2	0.880				
	BI3	0.893				
EC	EC1	0.877	0.900	0.901	0.930	0.769
	EC2	0.875				
	EC3	0.904				
	EC4	0.850				
KA	KA1	0.866	0.852	0.853	0.901	0.694
	KA2	0.856				
	KA3	0.841				
	KA4	0.765				
KAP	KAP1	0.875	0.863	0.865	0.907	0.709
	KAP2	0.826				
	KAP3	0.841				
	KAP4	0.826				
KS	KS1	0.875	0.884	0.887	0.915	0.683
	KS2	0.826				
	KS3	0.841				
	KS4	0.826				
	KS5	0.875				
PU	PU1	0.866	0.841	0.843	0.904	0.759
	PU2	0.859				
	PU3	0.888				
STS	ST1	0.872	0.896	0.896	0.928	0.762
	ST2	0.885				
	ST3	0.868				
	ST4	0.867				
SUST	SUST1	0.889	0.850	0.851	0.909	0.769
	SUST2	0.862				
	SUST3	0.880				

Table 4. Fornell-Larcker criterion

Constructs	BI	EC	KA	KAP	KS	PU	STS	SUST
BI	0.894							
EC	0.662	0.877						
KA	0.689	0.660	0.833					
KAP	0.581	0.610	0.612	0.842				
KS	0.693	0.656	0.687	0.669	0.826			
PU	0.675	0.735	0.615	0.578	0.579	0.871		
STS	0.598	0.646	0.497	0.460	0.532	0.499	0.873	
SUST	0.685	0.724	0.669	0.555	0.650	0.649	0.606	0.877

Table 5. Heterotrait-Monotrait

Constructs	BI	EC	KA	KAP	KS	PU	STS	SUST
BI								
EC	0.745							
KA	0.796	0.754						
KAP	0.667	0.691	0.714					
KS	0.784	0.733	0.790	0.763				
PU	0.784	0.843	0.726	0.678	0.667			
STS	0.674	0.720	0.569	0.522	0.595	0.574		
SUST	0.794	0.828	0.786	0.647	0.747	0.766	0.695	

Table 4 reports the results of discriminant validity based on the Fornell-Larcker criterion. The Fornell-Larcker Criterion and the Heterotrait-Monotrait ratio (HTMT) instruments were employed to evaluate the discriminant validity of the measurements [50]. According to the Fornell-Larcker criterion, the Square Root of the Average Variance Extracted (SQRT(AVE)) for each construct should be greater than its highest correlation with any other construct. The results show that all diagonal values are greater than the correlations between their corresponding constructs in the same row and column. Specifically, the SQRT(AVE)) values for BI (0.894), EC (0.877), KA (0.833),

KAP (0.842), KS (0.826), PU (0.871), STS (0.873) and SUST (0.877) all met the requirements for discriminant validity. Although this method is widely used, it has some limitations, such as a lack of statistical inference and an inability to detect violations of discriminant validity between constructs.

To address the above problems, the authors introduced an alternative solution called the Heterotrait-Monotrait Ratio (HTMT). The academic community quickly adopted this method and considered it a more reliable standard for assessing discriminant validity in measurement models involving latent constructs.

The HTMT index was calculated based on [51] a Multimethod Matrix (MTMM) [50]. This method assesses the extent to which indicators measuring a single construct differ from indicators measuring other constructs. HTMT is the ratio of the average correlation between indicators of two different constructs to the geometric mean of the average correlation within the same construct.

The appropriate HTMT threshold is usually 0.90 or less [52]. The results in Table 5 indicate that all HTMT values are below the 0.90 threshold, with the highest value of 0.796 (between KA and BI). This confirms that discriminant validity between latent constructs is well established, with each construct representing a distinct concept within the research model.

C. Hypothesis Model Testing

Table 6 presents the results of the PLS-SEM analysis, providing readers with important insights into the factors influencing the sustainable use of chatbots in higher education.

First, H1 and H2 were strongly confirmed, showing that expectation confirmation had a significant impact on both usefulness ($\beta = 0.735$, $p < 0.001$) and satisfaction ($\beta = 0.607$, $p < 0.001$). In contrast, H3 (PU → Satisfaction) is not supported ($\beta = 0.053$, $p = 0.372$), contrary to many previous studies. This helps students evaluate chatbots as useful but not necessarily satisfied, due to limitations in interaction capabilities, a lack of conversational naturalness, or poor support for complex requests. Nevertheless, both H4 and H5 were confirmed: usefulness ($\beta = 0.272$, $p < 0.001$) and satisfaction ($\beta = 0.203$, $p < 0.001$) positively influenced behavioral intention, indicating that both cognitive and affective factors are important in the distribution of long-term usage behavior. For the KM factors, H6 and H7 were supported ($\beta = 0.255$; $\beta = 0.236$, $p < 0.001$), indicating that chatbots that support knowledge sharing and acquisition well, such as providing learning materials, discussions, or quick answers, tend to keep students using them. Conversely, hypothesis H8 (Application of knowledge → BI) was not supported ($\beta = 0.016$, $p = 0.644$), indicating no connection between chatbot knowledge and practical learning tasks. Finally, hypothesis H9 was strongly supported ($\beta = 0.685$, $p < 0.001$), underscoring that behavioral intention is a central factor in establishing certainty about chatbot use.

In summary, the research results show that validation, along with knowledge sharing and reception, are core factors shaping long-term usage behavior. At the same time, the gap between usefulness and satisfaction is a limitation of knowledge application, revealing weaknesses that require attention.

Table 6. The PLS-SEM results

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Results
BI → SUST	0.685	0.685	0.034	20.205	0.000	Support
EC → PU	0.735	0.735	0.028	26.528	0.000	Support
EC → STS	0.607	0.606	0.051	11.794	0.000	Support
KA → BI	0.236	0.236	0.040	5.955	0.000	Support
KAP → BI	0.016	0.016	0.035	0.462	0.644	**Not** support
KS → BI	0.255	0.256	0.040	6.415	0.000	Support
PU → BI	0.272	0.271	0.036	7.648	0.000	Support
PU → STS	0.053	0.055	0.059	0.892	0.372	**Not** support
STS → BI	0.203	0.203	0.031	6.544	0.000	Support

D. Inner VIF Analysis Results

The results of the multi-collinearity among latent variables, using the Inner VIF coefficient, are shown in Table 7. The model can be considered statistically safe [53] if the VIF values are less than 3.0, indicating the absence of multicollinearity. All Inner VIF values are less than 3.0, with the highest value being 2.92, according to Table 7's statistics. This suggests that the independent variables in the model do not have a strong linear relationship. The absence of multicollinearity indicates that each independent latent variable contributes uniquely to explaining the dependent variable, thereby enhancing the structural model's accuracy and reliability. As a result, neither eliminating any independent variables nor creating a new model is necessary.

Table 7. Inner VIF analysis results

Constructs	BI	EC	KA	KAP	KS	PU	STS	SUST
BI								1.000
EC						1.000	2.172	
KA	2.298							
KAP	2.092							
KS	2.492							
PU	1.916						2.172	
STS	1.541							
SUST								

V. Discussion

A. Theoretical Contribution

First, the study develops a novel theoretical framework to explain the long-term deployment of AI chatbots in academic settings by integrating the Expectation-Confirmation Model (ECM) and Knowledge Management (KM). This innovative method integrates knowledge interaction skills and user psychology into a single model. Second, the study helps close the research gap between industrialized and developing nations by extending the application of these theories to the Vietnamese context, a developing market that has received limited attention in the area of digital transformation in education. Third, rather than utilizing the term "Knowledge Management" in a broad sense, the study significantly advances knowledge management theory by identifying three key components: information sharing, knowledge acquisition, and knowledge application. This opens a new research area on the interaction among technology, learning content, and learners' application capabilities, highlighting a possible gap between the knowledge acquired through chatbots and the capacity to apply it effectively in practice.

B. Managerial Implications

This study provides practical implications for the sustainable application of AI chatbots in higher education, particularly useful for school administrators, system designers, and educational technology professionals. The results show that, for chatbots to be truly useful, they must meet all users' initial expectations, as this alignment will influence users' perceptions of usefulness and enjoyment. Specifically, school administrators should ensure chatbots align with students' learning expectations by integrating them specifically into academic functions, such as course counseling, assignment guidance, and exam preparation materials, rather than deploying them as generic support tools. Furthermore, system designers should prioritize providing timely, accurate, and contextually relevant feedback by incorporating specialized knowledge bases and adaptive response mechanisms, enabling chatbots to support students' learning tasks more effectively. However, technical efficiency alone is insufficient; the experience must also be accessible, natural, and emotionally engaging to foster connection and trust. Beyond technical performance, chatbots should be designed with intuitive conversational interfaces and empathetic interactive features to enhance accessibility, trust, and emotional engagement. Finally, chatbots need to be regularly updated, listen to student feedback, and adapt more effectively to the diversity of ages, majors, and needs. Therefore, organizations should establish continuous monitoring and feedback mechanisms, such as periodic user reviews and iterative system updates, to ensure that chatbots consistently meet diverse academic and professional needs, as well as the evolving learning needs of students, thereby promoting long-term, sustainable use.

Through this study, we argue that expectation confirmation positively affects users' perceived usefulness and satisfaction, thereby enhancing their intention to use the system. More importantly, the findings demonstrate that sustainable chatbot use emerges from the interaction between post-adoption evaluation mechanisms (ECM) and knowledge-related processes (KM). While ECM explains why students feel motivated to continue using chatbots, KM clarifies how chatbots support learning through knowledge sharing, acquisition, and application, transforming motivation into sustained use.

The findings further indicate that behavioral intention is jointly influenced by both affective and cognitive factors, particularly through the mechanisms of knowledge acquisition and knowledge sharing. This result is consistent with post-adoption studies grounded in the Expectation–Confirmation Model (ECM), in which post-use evaluations play a central role in shaping users' affective responses and continuance intention toward technology use. In addition, consistent with [1], the knowledge management factors indicate that chatbots function not merely as information-delivery tools but also as learning-support infrastructures. However, knowledge application does not exhibit a direct effect on behavioral intention, reflecting inherent limitations of chatbots in facilitating higher-order knowledge transfer and complex learning tasks. This finding highlights an important boundary condition of the ECM–KM framework in educational contexts. It contributes to a more comprehensive theoretical understanding of the sustainability of AI-based learning technologies.

VI. Conclusion

This study develops the theory by demonstrating that sustainable chatbot use in higher education stems from the simultaneous operation of evaluation mechanisms after their application to knowledge management processes. By integrating ECM and KM, the findings show that satisfaction based on validation and knowledge support for learning activities is an additional pathway to the long-term sustainability of chatbots. In practice, the findings indicate that, to support sustainable educational transformation, universities should move beyond short-term chatbot deployment strategies and adopt ecosystem-level approaches that incorporate pedagogical integration, technological design, and governance policies. And chatbots can become reliable, long-term learning tools for students if they are personalized and user-friendly.

This study is subject to several limitations that should be acknowledged. The empirical data were collected exclusively from Vietnamese higher education institutions, where cultural learning norms, institutional practices, and levels of digital readiness may differ from those in other countries. Culturally, students are often accustomed to instructor-centered learning environments and may perceive AI-based chatbots primarily as informational support tools rather than as interactive learning partners [54]. Institutionally, the level of AI integration into curricula and the governance of educational technologies vary considerably across universities [55]. Technologically, differences in digital infrastructure and prior experience with AI systems may influence students' evaluations and continued use of chatbots [56]. Accordingly, the findings should not be generalized indiscriminately to higher education systems with different levels of digital maturity. Therefore, the generalizability of the ECM–KM framework beyond this context should be interpreted with caution.

Future studies should further extend the proposed model by testing the invariance and generalizability of the ECM–KM framework through cross-national comparisons or multigroup analyses across educational systems with varying levels of digital maturity, to assess the contextual role in shaping behavioral intention and the sustainable use of chatbots. The study did not measure students' prior chatbot use in detail, including the frequency and duration of use. Specifically, chatbot stress levels can influence learners' acceptance, perceived behavioral significance, and consistent use. Therefore, future studies should include more detailed reports of actual usage behavior that fully reflect the diversity of user experiences and conduct more rigorous tests of the proposed ECM–KM model. Future studies are also encouraged to adopt a longitudinal research design or cohort method to track changes in usage behavior over time. Adopting longitudinal research designs or mixed-method approaches would help clarify the transition from post-adoption evaluations (such as expectation confirmation and satisfaction) to long-term behavioral commitment, thereby strengthening the mediating role of Behavioral Intention within the model. Moreover, future research should incorporate additional variables reflecting interaction quality, personalization, social presence, AI ethics, and instructors' supportive roles to provide deeper explanations of the identified boundary conditions, particularly the gap between perceived usefulness and satisfaction, as well as the limitations of chatbots in supporting knowledge application and higher-order learning in higher education contexts.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

N.-H.D. conceptualized the study, supervised the entire research process, and provided theoretical guidance and critical revisions. H.A.V.T. conducted the empirical research, collected and analyzed the data, and contributed to drafting the manuscript. K.H.P.T. participated in data analysis and interpretation and assisted in manuscript writing and revision. T.Q.T.T. supported data collection, contributed to result interpretation, and provided editorial assistance during manuscript preparation. All authors read and approved the final version of the manuscript for submission.

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