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AI Reuse Intention: A Study of Finance Students in Hochiminh University of Banking

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ABSTRACT
This study investigates the factors influencing students' intention to continue using AI chatbots at Ho Chi Minh University of Banking (HUB). Drawing on the UTAUT2 model, the research examines the effects of Perceived Ease of Use, Perceived Usefulness, Social Influence, Hedonic Motivation, Habit, Functional Congruence, and Perceived Vulnerability on Behavioral Intention. Data was collected from 248 students who had previously used AI chatbots. The analysis reveals that Perceived Usefulness is the strongest predictor of continued use intention, followed by Hedonic Motivation and Habit. Social Influence does not significantly impact intention. The findings provide valuable insights for educational institutions and financial organizations in developing strategies to promote AI adoption among future professionals in the banking and finance sector

Keywords: *Chatbot AI, ChatGPT, UTAUT2 model, behavioural intention, student, HUB*

1. INTRODUCTION

Artificial intelligence (AI) offers substantial advantages for the banking, financial services, and insurance (BFSI) sector, ultimately increasing efficiency and improving risk management (Narang, Vashisht, & Bajaj, 2024). However, sustainable competitive advantage requires strategic human capital development beyond mere technological adoption. Najem et al. (2024) emphasize that successful AI integration hinges on a clear strategic vision, an innovative culture, and robust data analytics. Gujar et al. (2024) further underscore that long-term benefits depend on investments in both talent and infrastructure. These organizational priorities shape the interaction of future professionals with AI. Therefore, fostering the intention to continue AI usage among students aspiring to BFSI careers is paramount, as they represent the future workforce significantly influencing AI application in these institutions. Ho Chi Minh City, Vietnam's largest economic hub and a major center for human resource development (Trần Quang Quý, 2024), with its reputable Ho Chi Minh City Banking University, offers a relevant context to study AI post-adoption behavior in education. Understanding these multifaceted factors is crucial for both academic inquiry and practical application. Theoretically, this study contributes to the nascent literature on AI post-adoption behavior in education, specifically within the Vietnamese context. Practically, its insights can inform financial institutions in aligning recruitment, training, and innovation strategies to effectively engage with AI-aware professionals, which is indispensable for maintaining competitiveness and resilience in an increasingly digital financial landscape.

The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2003, 2012), integrating earlier models, identifies key factors influencing technology adoption, including price value, hedonic motivation, and habit, providing a comprehensive framework for studying technology acceptance. Reuse intention, similar to continued usage intention and e-loyalty (Chen et al., 2013; Bhattacherjee, 2001), describes a user's intent to continue using new information technology.

Social Influence (SI) impacts perceived usefulness (Performance Expectancy – PE) and ease of use (Effort Expectancy – EE) (Davis, 1989), influencing technology adoption across platforms like gaming (Hsu & Lu, 2004), messaging apps (Rice et al., 1990), and websites (Hsu & Lin, 2008), and significantly affecting continued use of digital services (Dai & Cheng, 2022; Kim & Srivastava, 2007; Tran, 2023; Tran et al., 2024). Performance Expectancy (PE), the perceived benefits of technology use, and Effort Expectancy (EE), the perceived ease of use (Venkatesh et al., 2003; Adams et al., 1992; Agarwal & Karahanna, 2000), are central to technology acceptance. In chatbots, PE predicts adoption for fast information and academic support (Al-Emran et al., 2024), while EE positively influences continued use when systems are user-friendly (Chang et al., 2012; Nath et al., 2013; Nguyen Thi et al., 2022; Wen et al., 2011).

Facilitating Conditions (FC), external resources easing technology use (Venkatesh et al., 2012), increase usage intent with perceived support (Im et al., 2011; Thompson et al., 1991). Habit (HBT), automatic behavior tendency (Kim et al., 2005; Limayem et al., 2007), also predicts usage; familiarity with smart learning apps can ease chatbot adoption. Perceived Value (PV), the cost-benefit tradeoff, significantly affects adoption (Venkatesh et al., 2012; Lyu & Zhang, 2021; Guo et al., 2022), as does Hedonic Motivation (HM), the enjoyment derived from use (Anderson et al., 2014; Chang et al., 2012), especially in student and consumer contexts.

Shoufan (2023) highlights students' positive perceptions of AI tools like ChatGPT (usefulness, ease of use, engagement) but suggests UTAUT2 over TAM for deeper analysis. Raza et al. (2021) successfully applied UTAUT2 in a student context, explaining significant behavioral variance, justifying its adoption to assess AI reuse intention among finance students.

2. RESEARCH METHOD AND MODEL

This study employs a mixed-methods approach, with qualitative research informing the research model and measurement scales, and quantitative research dominating to test the model and hypotheses. Data analysis utilizes SPSS 26 and SmartPLS 4.0. The UTAUT2 model is applied to examine factors influencing AI chatbot reuse among finance students at Ho Chi Minh City Banking University. Constructs are measured using five-point Likert scales. Analysis includes descriptive statistics and multicollinearity assessment via VIF. Measurement and structural models are evaluated in SmartPLS, following Hair et al. (2021), assessing outer loadings, AVE, reliability, and discriminant validity. The structural model is tested using PLS-SEM to analyze complex relationships. Based on the UTAUT2 theory and previous studies to develop a model of chatbot usage intention, the following seven hypotheses and proposed research model have been developed:

H1: Perceived Ease of Use (EE) has a positive effect on Behavioral Intention (BI).

H2: Perceived Usefulness (PE) has a positive effect on Behavioral Intention (BI).

H3: Social Influence (SI) has a positive effect on Behavioral Intention (BI).

H4: Hedonic Motivation (HM) has a positive effect on Behavioral Intention (BI).

H5: Habit (HBT) has a positive effect on Behavioral Intention (BI).

H6: Functional Congruence (FC) has a positive effect on Behavioral Intention (BI).

H7: Perceived Vulnerability (PV) has a negative effect on Behavioral Intention (BI).

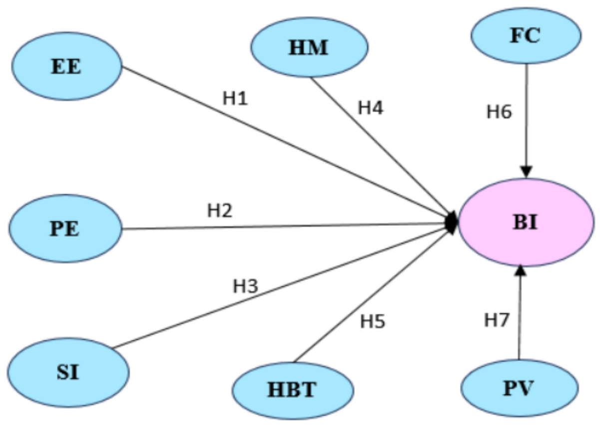

Figure 1: Proposed theoretical model

3. RESULT

Data was collected through an online survey using Google Forms, which was distributed to students in Ho Chi Minh City Banking University. The survey participants were individuals who had previously used AI chatbots. Therefore, the research team distributed the survey to over 300 respondents and received 248 valid responses. This sample size fully meets the aforementioned requirements. The demographic information of the respondents is presented in Table 1.

Table 1. Demographic Characteristics

Characteristic		Frequency	Percent (%)
Gender	Male	99	39,9
	Female	149	60,1
Academic Year	Year 1	61	24,6
	Year 2	45	18,1
	Year 3	108	43,5
	Year 4	34	13,7
N = 248			

Outer Loadings: Items PE1, PE2, and PE7 were removed due to outer loadings below 0,7. All remaining items demonstrated acceptable loadings. This indicates that the items PE1, PE2, and PE7 did not strongly contribute to their respective construct (Perceived Ease of Use) and were therefore excluded to improve the model's validity. The remaining items in Table 2 show a strong relationship with their constructs.

Psychometric Properties of the Measurement Model: The measurement model generally demonstrates robust psychometric properties. Item loadings for all constructs are high (0.704 - 0.926), and internal consistency, as indicated by Cronbach's alpha (0.716 - 0.909) and Composite Reliability (0.840 - 0.943), is satisfactory across all constructs. Convergent validity is also supported with AVE values above 0.50 (0.585 - 0.847). Regarding multicollinearity, while most Variance Inflation Factor (VIF) values for the items of other constructs are below the threshold of 3.0. However, items HM1 (VIF = 3.129) and HM3 (VIF = 3.061) slightly exceed this threshold. This suggests potential higher collinearity for these specific indicators, warranting careful consideration in subsequent analysis.

Table 2. Official measurement scales of the variables in the research model

Code	Content	Source
Expectation of performance - PE		
PE3	I feel I need more guidance to understand the benefits of using an AI chatbot	Davis & ctg (1989); Dai & Cheng (2022)
PE4	Using an AI chatbot has helped me better understand the topics I'm interested in	
PE5	I believe that AI chatbots can improve my performance in completing assignments and academic projects.	
PE6	I can save a lot of time searching for information when using an AI chatbot.	
PE8	Overall, AI chatbots bring a lot of value to my learning proces.	
PE9	AI chatbots help me identify and develop the professional skills necessary for my career.	
Expectation of effort - EE		
EE1	I can easily learn how to use an AI chatbot.	Nguyen Thị & ctg (2022); Davis & ctg (1989)
EE3	I find it easy to use AI chatbots for learning various skills.	
EE4	Using an AI chatbot is similar to other applications I currently use..	
Facilitating Conditions - FC		
FC1	There are sufficient instructions and support information to help me get started with learning how to use AI chatbots.	Thompson & ctg (1991)
FC2	AI chatbots like ChatGPT are easy to install and use, even for those without technical expertise.	
FC3	I am equipped with the necessary knowledge and skills to use AI chatbots easily.	
Habit –HBT		
HBT1	Even if not required, I still find it necessary to use AI chatbots.	Venkatesh & ctg (2012)
HBT2	Using AI chatbots to search for information has become almost a habit.	

Code	Content	Source
HBT3	I always use AI chatbots whenever needed.	
Social Influence - SI		
SI1	I often hear my friends talking about using chatbots or AI technology in learning.	Venkatesh and Davis (2000) và Tran (2023)
SI2	My teachers often recommend using AI chatbots for studying.	
SI3	The general trend of using AI chatbots in the community influences my decision to use them.	
Hedonic Motivation – HM		
HM1	How enjoyable do you find interacting with an AI chatbot?	Venkatesh & ctg (2012)
HM2	I enjoy the level of interaction that a chatbot provides.	
HM3	I really like the responses that AI chatbots provide.	
Price Value – PV		
PV1	How do you evaluate the reasonableness of the cost of using an AI chatbot compared to the value it provides?	Venkatesh & ctg (2012)
PV2	Compared to hiring a tutor or attending classes at a center, do you think the cost of an AI chatbot is reasonable?	
PV3	Considering the learning and informational support that AI chatbots offer, do you feel its price is reasonable for you personally?	
Behavioural Intention - BI		
BI1	I am fully willing to accept and use AI chatbots for learning if they are truly helpful to my field of study.	Venkatesh & ctg (2012)
BI2	I think I can complete most of my tasks through an AI chatbot.	
BI3	I will use AI chatbots to look up information in my daily life.	
BI4	I will use AI chatbots for studying and work in the near future.	
BI5	I want to explore more features and applications of AI chatbots in learning.	

Source: Compiled and proposed by the author

Table 3 BOOTRAP 5000

Hypothesis		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Result
H1	EE -> BI	0,099	0,099	0,039	2,539	0,011	Accept
H2	FC -> BI	0,101	0,102	0,041	2,455	0,014	Accept
H3	HBT -> BI	0,213	0,215	0,043	4,915	0,000	Accept
H4	HM -> BI	0,243	0,241	0,048	5,056	0,000	Accept
H5	PE -> BI	0,338	0,338	0,059	5,697	0,000	Accept
H6	PV -> BI	0,101	0,101	0,042	2,399	0,016	Accept
H7	SI -> BI	0,064	0,064	0,043	1,464	0,143	Unaccept

Source: Results of data analysis using SmartPLS

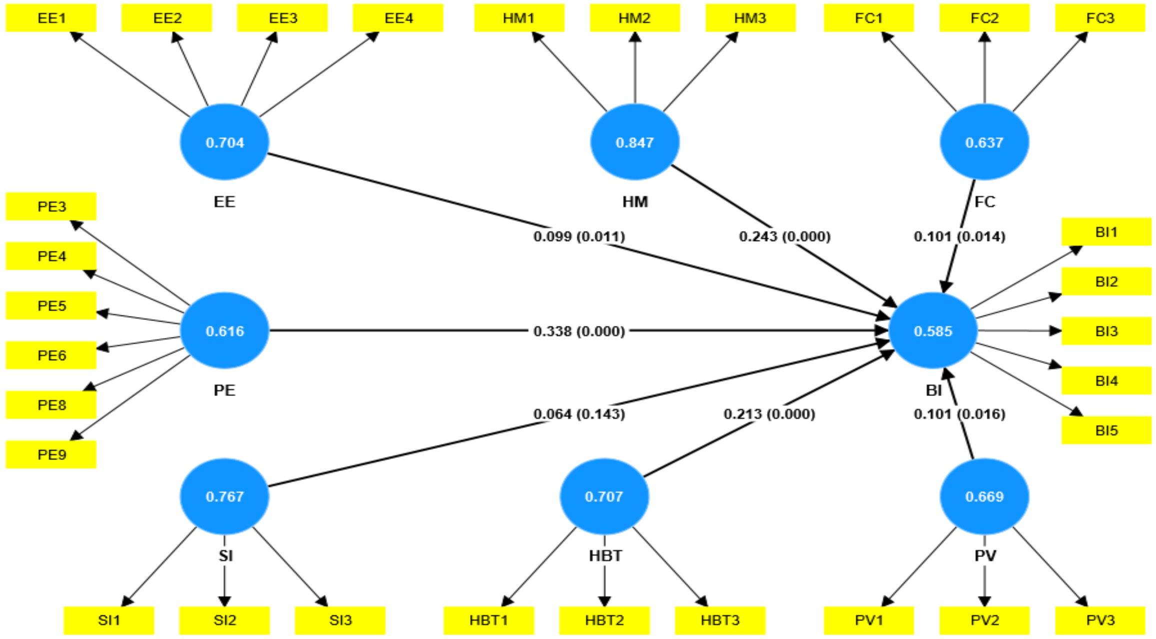

Figure 2. Students' behavioral intention to continue using AI chatbots in HUB

4. CONCLUSION AND IMPLICATIONS

The research findings indicate that several factors influence students' intention to continue using AI chatbots at Ho Chi Minh City Banking University. The analysis, based on a sample of 248 students, reveals that Perceived Usefulness (PE) is the strongest predictor of continued use intention ($\beta = 0.338$, $p < 0.001$), followed by Hedonic Motivation (HM) ($\beta = 0.243$, $p < 0.001$) and Habit (HBT) ($\beta = 0.213$, $p < 0.001$). Perceived Ease of Use (EE) ($\beta = 0.099$, $p = 0.011$), Functional Congruence (FC) ($\beta = 0.101$, $p = 0.014$), and Perceived Vulnerability (PV) ($\beta = 0.101$, $p = 0.016$) also positively affect intention, while Social Influence (SI) ($\beta = 0.064$, $p = 0.143$) does not have a significant impact. Thus, Perceived Usefulness has the strongest influence on the students' intention to reuse AI chatbots. Students who perceive AI chatbots as highly useful for their academic tasks are most likely to form a strong intention to continue using them. The model explained a substantial portion of the variance in Behavioral Intention (BI), with an R-squared value of 0.753. This study explores the factors influencing students' intention to continue using AI chatbots, utilizing the UTAUT2 model as a framework. Consistent with Raza et al. (2021), our findings confirm the model's applicability in educational technology research. Both studies demonstrate UTAUT2's effectiveness in explaining student technology acceptance. Notably, Perceived Usefulness strongly drives intention, aligning with Shoufan (2023), which highlights AI tool usefulness. However, while Raza et al. (2021) examined Learning Management Systems (LMS) during the pandemic, this research focuses on AI chatbots, showcasing UTAUT2's adaptability to specific AI applications. A key difference emerges in the non-significant influence of Social Influence, unlike some UTAUT2 applications, suggesting that AI chatbot adoption may be attributed to internally motivated behavioral intentions. Furthermore, the study extends UTAUT2 by identifying Perceived Vulnerability as a significant factor, unique to AI acceptance concerns. In conclusion, this research largely confirms UTAUT2's validity while also demonstrating its extension and nuanced application in the context of AI chatbots, compared to previous studies.

To enhance continued chatbot use intention, several implications emerge: Firstly, to maximize the impact of Perceived Usefulness (PE) ($\beta = 0.338$, $p < 0.001$), educators should integrate chatbots into core academic tasks to clearly demonstrate their value. Secondly, to leverage Hedonic Motivation (HM) ($\beta = 0.243$, $p < 0.001$), chatbot design should prioritize engagement through interactive elements and personalized feedback. Thirdly, to cultivate Habit (HBT) ($\beta = 0.213$, $p < 0.001$), strategies should encourage habitual use through consistent integration and rewards. Fourthly, while Perceived Ease of Use (EE) ($\beta = 0.099$, $p = 0.011$) and Functional Congruence (FC) ($\beta = 0.101$, $p = 0.014$) have a smaller impact, ensuring user-friendliness and tailored functionalities remains important. Fifthly, to address Perceived Vulnerability (PV) ($\beta = 0.101$, $p = 0.016$), providing clear information on data privacy and responsible use is essential. Finally, given the non-significant effect of Social Influence (SI) ($\beta = 0.064$, $p = 0.143$), emphasizing individual benefits and intrinsic value is likely more impactful.

While the research has yielded several positive results as initially intended, it is subject to certain limitations. The convenience sampling method used may not fully represent the entire student population. Additionally, the independent variables in the model explain only 75.3% of the variance in the dependent variable. Therefore, future research should consider incorporating additional factors, new observed variables, and refined measurement scales into the model. Furthermore, improvements in the sampling method are needed to enhance the representativeness of the study's findings.

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