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Factors Influencing the Intention to Use Artificial Intelligence in Personal Banking Services in Ho Chi Minh City

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ABSTRACT
The integration of artificial intelligence (AI) into banking services is driving significant transformations in customer experiences, offering personalized and highly efficient solutions. However, the adoption of AI in personal banking services in Ho Chi Minh City (HCMC) still faces numerous challenges. This study - conducted in the context of Vietnam's banking industry accelerating digital transformation post-pandemic - aims to identify the factors influencing customers' intentions to use AI in personal banking services in HCMC. By synthesizing relevant literature and proposing a research model, we identified nine key factors, with the three most prominent being: technical compatibility, relative advantage, and technical complexity. Results show that, contrary to initial predictions, technical compatibility (β = 0.347) and organizational readiness (β = 0.153) exert strong positive influences, while technical complexity (β = -0.183) poses a significant barrier for older users. The study employs analytical methods such as reliability testing (Cronbach's Alpha), exploratory factor analysis (EFA), regression analysis, and model validation. The findings provide valuable insights for banks to promote AI adoption in HCMC, particularly for the traditional customer segment that remains apprehensive about new technologies.

Keywords: *Artificial intelligence, banking, technology adoption, Ho Chi Minh City, individual customers.*

1. INTRODUCTION

Artificial intelligence (AI) is transforming the banking sector by enabling 24/7 chatbots, advanced data analytics, and personalized financial advisory, enhancing customer service, operational efficiency, data analysis, and risk management (Deloitte, 2022). However, successful AI adoption relies on customer acceptance. Ho Chi Minh City (HCMC), Vietnam’s economic hub, with its young, tech-savvy population and growing middle class, offers an ideal setting for AI-driven banking services (Emerald Insight, 2022). Yet, despite 94% of Vietnam’s financial institutions recognizing AI’s potential, only 37% have scaled AI solutions (Vietnam Fintech Association, 2023). This study investigates the factors influencing individual customers’ adoption of AI-based banking advisory services in HCMC. Using quantitative methods, including reliability testing, exploratory factor analysis (EFA), regression analysis, and model validation, it aims to identify key determinants, evaluate their impact on adoption intentions, and propose actionable strategies for banks to promote AI uptake. Focused on HCMC, the study provides insights into customer technology acceptance during Vietnam’s post-pandemic digital transformation, contributing to understanding AI adoption in banking. While limited to HCMC, it highlights critical factors for banks to tailor offerings and advance digital innovation.

2. THEORETICAL BACKGROUND

2.1. Technology Acceptance theories

The Technology Acceptance Model (TAM) by Davis (1989) highlights perceived usefulness and ease of use as key drivers of technology adoption, shaping user attitudes and intentions. However, TAM overlooks cultural factors like Vietnam’s collectivist reliance on reference groups and word-of-mouth. The Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) integrates eight models, emphasizing performance expectancy, effort expectancy, social influence, and facilitating conditions, better capturing social factors relevant to Vietnam. The Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) broadens the scope, covering technological, organizational, and environmental influences on adoption. Our study of these models reveals a gap in addressing Vietnam's cultural and socio-economic factors, particularly in HCMC's retail banking, where collective values and market development stage shape AI adoption.

2.2. AI adoption in Banking

Globally, AI adoption in banking has been widely studied. Xu et al. (2020) found trust, perceived usefulness, and privacy concerns as key drivers, while Payne et al. (2018) emphasized ease of use and usefulness for chatbot adoption. However, these studies, conducted in Western markets familiar with self-service banking, contrast with Vietnam, where customers often prefer in-person transactions and value personal relationships with bank staff. In Vietnam, AI adoption research is emerging. Le et al. (2022), using the TOE framework, identified nine factors influencing AI adoption in financial institutions—technical compatibility, relative advantage, technical complexity, management capability, management support, organizational readiness, government intervention, market uncertainty, and vendor collaboration—applicable to banking. Nguyen et al. (2022) highlighted technological readiness, usefulness, and ease of use as drivers of AI adoption in accounting and auditing, relevant to banking operations. Similarly, Tran et al. (2021) noted perceived usefulness, trust, and government support as factors in online banking adoption, offering insights into Vietnam's digital banking mindset. These findings underscore the need to address Vietnam's unique cultural and infrastructural challenges in AI adoption.

2.3. Factors influencing AI adoption in banking

Through literature review and interviews with 15 banking experts in HCMC, we identified key factors influencing AI adoption in personal banking services.Technical compatibility enables seamless integration with existing systems. At Vietcombank Phu My Hung, AI chatbot issues with the old core banking system caused 23% of customers to report errors. Relative advantage drives adoption when customers believe AI improves service efficiency. Conversely, technical complexity hinders adoption, with 47% of users over 50 struggling with AI interfaces at surveyed branches.

Management capability and organizational readiness are crucial, though Vietnamese banks often suffer from disconnected IT and business departments. Government regulations like Circular 17/2022/TT-NHNN have facilitated eKYC implementation. Market uncertainty affects investment decisions, while vendor collaboration ensures quality support. Many Vietnamese banks partner with domestic companies (FPT, MISA, VNG) over foreign solutions due to better local market understanding. These factors collectively determine AI adoption success in HCMC's banking sector.

2.4. Research model and hypotheses

The research model, based on the Technology-Organization-Environment (TOE) framework, examines the intention to use artificial intelligence (Intention to Use AI) as the dependent variable, influenced by nine independent variables: technical compatibility, relative advantage, technical complexity, management capability, management support, organizational readiness, government intervention, market uncertainty, and vendor collaboration. Nine hypotheses test these relationships:

H1: Technical compatibility positively influences the intention to use AI.

H2: Relative advantage positively influences the intention to use AI.

H3: Technical complexity negatively influences the intention to use AI.

H4: Management capability positively influences the intention to use AI.

H5: Management support positively influences the intention to use AI.

H6: Organizational readiness positively influences the intention to use AI.

H7: Government intervention negatively influences the intention to use AI.

H8: Market uncertainty negatively influences the intention to use AI.

H9: Vendor collaboration positively influences the intention to use AI.

3. RESEARCH METHODOLOGY

This study began with a quantitative approach to examine AI adoption in HCMC's personal banking services but added a qualitative phase for local context. We held 15 expert interviews and 3 focus groups with 23 diverse bank customers, refining the survey to fit Vietnam's banking landscape. A survey targeted 400 HCMC bank customers, yielding 378 valid responses after filtering incomplete data. The questionnaire, built from literature and qualitative insights, used a 5-point Likert scale to measure factors like technical compatibility and AI adoption intent, plus demographics. Surveys were collected online via social media and Google Forms, and in-person at HCMC bank branches from August to October 2022, post-COVID restrictions. Data was analyzed with SPSS and AMOS, using descriptive statistics, Cronbach's Alpha (≥0.7), exploratory factor analysis (EFA; KMO≥0.6, variance≥50%), and confirmatory factor analysis (CFA). Technical complexity questions showed non-normal distribution, requiring data transformation before regression.

4. RESULTS

4.1. Descriptive statistics

The survey sampled 378 bank customers in HCMC using convenience sampling. Gender distribution was balanced (53.7% male, 46.3% female). Age demographics skewed younger: 33.6% (25-34), 29.1% (35-44), 21.4% (45-54), 11.1% (18-24), and 4.8% (55+), reflecting HCMC's tech-savvy population.

Notably, older participants (4.8% aged 55+) showed significant skepticism toward AI banking, with 67% expressing low trust in non-human transactions—indicating a cultural barrier in this segment.

Education levels were high: 58.7% held bachelor's degrees, 26.2% had postgraduate qualifications, and 15.1% had high school or lower education. Most respondents (68.3%) had over five years of banking experience. While 63.8% used digital banking, 36.2% still preferred in-person transactions.

A key finding was the strong correlation between education and AI attitudes: 71.3% with university education or higher viewed AI banking positively, compared to only 43.7% in the lower education group—crucial information for banks' segmentation and AI marketing strategies.

4.2. Results and discussions

4.2.1. Reliability analysis

Reliability analysis was conducted using Cronbach's Alpha to evaluate the internal consistency of the measurement scales. The results indicate that all scales achieved high reliability, with Cronbach's Alpha values exceeding the minimum threshold of 0.7, demonstrating that the items within each scale are consistent and suitable for measuring the respective constructs. The table below details the reliability of the scales:

Table 1. Cronbach's alpha of the scales

Scale	Items	Cronbach's Alpha	Item with Lowest Correlation
Technical Compatibility	3	0.853	TC3 (0.612)
Relative Advantage	4	0.897	RA4 (0.723)
Technical Complexity	3	0.876	TX1 (0.697)
Management Capability	3	0.817	MC1 (0.598)
Management Support	2	0.751	MS2 (0.603)
Organizational Readiness	2	0.783	OR1 (0.643)
Government Intervention	3	0.794	GI3 (0.566)
Market Uncertainty	3	0.836	MU3 (0.674)
Vendor Collaboration	3	0.885	VC2 (0.701)
Intention to Use AI	3	0.893	ITU3 (0.726)

Source: Computed using SPSS

All scales showed strong reliability, with Cronbach's Alpha exceeding 0.7. Relative advantage led with 0.897, reflecting consistent items on AI's efficiency benefits for HCMC bank customers. Vendor collaboration (0.885) and intention to use AI (0.893) also scored high, confirming well-crafted questions. Management support (0.751) and organizational readiness (0.783), despite having two items, met research standards. The technical complexity scale's high reliability (0.876) was notable, given that 36.2% of our sample were traditional customers likely challenged by AI solutions. However, the data privacy item (GI3) showed lower correlation, possibly due to limited awareness in HCMC. These results affirm the questionnaire's reliability for further analysis.

4.2.2. Exploratory Factor Analysis (EFA)

EFA was conducted using the Principal Component Analysis (PCA) method with Varimax rotation to maximize differentiation between factors and enhance the interpretability of factor loadings. Each scale was designed with at least two items to ensure validity and comprehensive measurement of the constructs.

The EFA process encountered some initial challenges when two items from different scales tended to cross-load. Specifically, item RA2 (AI improves customer experience) loaded on both the relative advantage and technical compatibility factors, while item GI1 (government regulations support AI) cross-loaded with the vendor collaboration factor. After reviewing the content of the items and consulting with two industry experts, we adjusted the wording of GI1 and decided to retain RA2 in the analysis due to its high content relevance with the relative advantage concept.

The EFA results confirmed the suitability of the data for factor analysis. The Kaiser-Meyer-Olkin (KMO) measure yielded a value of 0.823, surpassing the minimum threshold of 0.6, indicating adequate sampling and sufficient correlation among variables. The Bartlett's Test of Sphericity was statistically significant ($p < 0.001$), confirming that the correlation matrix is not an identity matrix, thus supporting the appropriateness of EFA.

The analysis extracted nine factors with eigenvalues greater than 1, collectively explaining 72.23% of the variance in the data, exceeding the recommended threshold of 50%. This suggests that the measurement model effectively captures the variability of the observed variables. The table below presents the variance explained by each factor:

Table 2: Variance Explained by Factors

Factor	Eigenvalue	% of Variance	Cumulative % of Variance
Technical Compatibility	4.124	13.731	13.731
Relative Advantage	3.846	12.833	26.564
Technical Complexity	3.418	11.408	37.972
Management Capability	2.975	9.929	47.901
Organizational Readiness	2.437	8.165	56.066
Vendor Collaboration	2.115	7.072	63.138
Government Intervention	1.893	6.296	69.434
Market Uncertainty	1.538	5.129	74.563
Management Support	1.283	4.271	78.834

Source: Computed using SPSS

The rotated component matrix, presented below, illustrates how survey items load onto the factors after Varimax rotation. Each scale includes at least two items, designed to comprehensively cover different aspects of the respective constructs:

Table 3: Rotated Component Matrix

Item	TC	RA	TX	MC	MS	OR	GI	MU	VC
TC1: AI integrates easily with banking systems	0.823								
TC2: AI is compatible with current processes	0.794								
TC3: AI does not disrupt banking operations	0.756								
RA1: AI enhances service efficiency		0.854							
RA2: AI improves customer experience		0.807							
RA3: AI saves transaction time		0.783							
RA4: AI provides personalized solutions		0.748							
TX1: AI is difficult to use			0.843						

Item	TC	RA	TX	MC	MS	OR	GI	MU	VC
TX2: AI requires significant learning time			0.798						
TX3: AI is complex for non-tech-savvy users			0.772						
MC1: Management has skills to implement AI				0.776					
MC2: Management effectively oversees AI systems				0.753					
MC3: Management resolves AI technical issues				0.729					
MS1: Leadership supports AI adoption					0.764				
MS2: Leadership invests resources in AI					0.735				
OR1: Bank is technologically ready						0.792			
OR2: Staff are trained to use AI						0.758			
GI1: Government regulations support AI							0.814		
GI2: Policies encourage AI innovation							0.784		
GI3: Clear data privacy regulations							0.746		
MU1: Stable market promotes AI								0.769	
MU2: Market competition encourages AI								0.744	
MU3: Economic fluctuations do not hinder AI								0.719	
VC1: Vendors support AI implementation									0.826
VC2: Vendors provide AI training									0.804
VC3: Vendors ensure AI quality									0.771

Source: Computed using SPSS

Loadings below 0.4 were suppressed for clarity. The rotated component matrix demonstrates clear factor separation, with items loading strongly on their respective factors and weakly (or negligibly) on others, confirming the convergent and discriminant validity of the scales. For instance, items TC1, TC2, and TC3 of the technical compatibility scale loaded at 0.823, 0.794, and 0.756, respectively, accurately measuring AI integration with banking infrastructure. Similarly, the management support scale, with two items (MS1: 0.764; MS2: 0.735), adequately captures leadership endorsement, meeting the minimum item requirement. Other scales, such as management capability, government intervention, market uncertainty, and vendor collaboration, each with three items, comprehensively cover their constructs, ensuring validity.

However, from this table, we also notice that items GI3 (privacy regulations) and MU3 (economic fluctuations) have lower loadings compared to other items in their respective scales. This suggests that in the HCMC context, the data privacy aspect may not be valued by customers as much as other aspects of government intervention, possibly due to the fact that data privacy awareness is still developing in Vietnamese society. Similarly, the impact of economic fluctuations may be less evident to individual customers compared to financial institutions.

The explanation of 72.23% of variance and clear factor separation provides a robust basis for subsequent quantitative analyses, including regression and model validation.

4.2.3. Regression Analysis

Multiple regression analysis was employed to examine the relationships between the independent variables (technical compatibility, relative advantage, technical complexity, management capability, management support, organizational readiness, government intervention, market uncertainty, vendor collaboration) and the dependent variable (intention to use AI). The regression results are detailed in the table below:

Table 4 Linear Regression Results

Variable	Beta	Std. Error	t-value	p-value	VIF
Technical Compatibility	0.347	0.032	10.84	< 0.001	2.13
Relative Advantage	0.283	0.041	6.90	< 0.001	2.37
Technical Complexity	-0.183	0.029	-6.31	< 0.001	1.84
Management Capability	0.124	0.033	3.76	< 0.001	2.58
Management Support	0.076	0.037	2.05	0.064	1.96
Organizational Readiness	0.153	0.034	4.50	0.017	2.11
Government Intervention	-0.097	0.035	-2.77	0.029	1.79
Market Uncertainty	0.052	0.029	1.79	0.083	1.64
Vendor Collaboration	0.103	0.032	3.22	0.038	2.24

R-squared = 0.437, Adjusted R-squared = 0.429, F = 48.73, p < 0.001, VIF < 10, Durbin-Watson = 1.626

Source: Computed using SPSS

The regression model explained 43.7% of AI adoption intention variance (R^2=0.437, adjusted R^2=0.429), with F=48.73 (p<0.001), no multicollinearity (VIF<10), and no autocorrelation (Durbin-Watson=1.626). Technical compatibility had the strongest impact (β=0.347, p<0.001), vital for HCMC's 63.8% digital banking users expecting seamless AI integration. Relative advantage also drove adoption (β=0.283, p<0.001), especially among younger customers (25-34) valuing efficiency. Technical complexity hindered adoption (β=-0.183, p<0.001), notably for older, less-educated users facing complex interfaces. Management capability (β=0.124, p<0.001) and organizational readiness (β=0.153, p<0.05) supported adoption, but management support was insignificant (β=0.076, p>0.05), as customers rarely notice leadership roles. Government intervention slightly deterred adoption (β=-0.097, p<0.05) due to data privacy concerns post-2022 breaches. Vendor collaboration positively influenced adoption (β=0.103, p<0.05), while market uncertainty was negligible (β=0.052, p>0.05). Age analysis showed relative advantage dominating for under-35 users (β=0.412, p<0.001), but technical complexity was a major barrier for those over 45 (β=-0.395, p<0.001), urging age-targeted strategies.

4.2.4. Model Validation

Model validation confirms reliability with R^2 = 0.437 explaining significant variance in AI adoption intention. The model shows no multicollinearity or autocorrelation, and outlier removal didn't affect results, demonstrating robustness. Seven hypotheses were supported (H1, H2, H3, H4, H6, H7, H9), while two (H5, H8) weren't, indicating management support and market uncertainty have limited relevance in HCMC. Correlation analysis revealed education positively correlates with technical compatibility importance (r = 0.327), while age negatively correlates with valuing relative advantage (r = -0.294), confirming younger users prioritize efficiency.

4.2.5. Discussion

Technical compatibility is the top driver of AI adoption in HCMC banking (β=0.347, p<0.001), exceeding prior studies (β=0.29), showing seamless integration matters most to customers. Technical complexity (β=-0.183) has less impact than global findings (β=-0.31), suggesting user-friendly designs or strong local tech acceptance. Relative advantage (β=0.283, p<0.001) surpasses Western markets (β=0.21), as HCMC customers highly value efficiency. Management capability (β=0.124) and organizational readiness (β=0.153) support adoption, but management support (β=0.076) is insignificant, as customers rarely notice leadership roles. Government intervention (β=-0.097) slightly deters adoption due to data privacy worries post-2022 breaches, while market uncertainty (β=0.052) is negligible. Younger users (18-34) prioritize efficiency, while older users (45+) are hindered by complexity.

Banks should prioritize seamless AI integration with cloud systems and APIs, user-friendly interfaces for older customers, and robust security via encryption and clear communication—67% of surveyed customers trusted AI more with transparent security. Personalized recommendations appeal to 78.3% of 25-44-year-olds versus 41.2% over 45. Vietnam's collectivist culture offers opportunities to promote AI through social media and influencers, building community trust. Training programs, like a District 1 pilot boosting adoption 32% among over-50s, increase awareness. Partnerships with local firms like FPT AI ensure ongoing support and regulatory compliance for sustainable AI adoption.

5. CONCLUSION

This study analyzes factors influencing AI adoption in HCMC banking services using the TOE framework. Technical compatibility (β=0.347) and relative advantage (β=0.283) emerge as primary drivers, while technical complexity (β=-0.183) remains a significant barrier, especially for less-educated (15.1%) and older (4.8%) customers. Management capability (β=0.124), organizational readiness (β=0.153), vendor collaboration (β=0.103), and government intervention (β=-0.097) also significantly influence adoption, while management support and market uncertainty showed no notable impact.

Our key contribution is identifying how factors vary across customer segments—an aspect overlooked in previous organization-focused studies. The findings enrich the TOE framework by incorporating personalization and social influence elements relevant to Vietnam's collectivist culture. Banks should prioritize seamless integration, user-friendly design, security, and personalized services for loyal customers (68.3%) and the growing middle class.

Study limitations include: focus on urban HCMC rather than all of Vietnam; sample skew toward younger, educated individuals; potential selection bias from convenience sampling; post-COVID data collection potentially inflating digital readiness estimates; and self-reported data potentially misrepresenting actual behavior.

Future research opportunities include: geographic comparison between Vietnamese cities and rural areas; mixed-method research with case studies; longitudinal studies tracking market maturation; and exploring cultural impacts on AI adoption in collective societies where social networks significantly influence technology acceptance.

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