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Behavioral Intention and User Behavior Toward AI-Based Features in Mobile Banking: Evidence from Indonesia

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Abstract: The rapid development of technology, particularly Artificial Intelligence (AI) forces industries to adapt and utilize it as it makes operations efficient. In the Indonesian banking industry, AI has increasingly been implemented in several features such as AI Chatbots for Customer Service, AI-Based Personal Financial Assistant, AI Credit Scoring and Loan Approval, AI Security Systems, and Robo Advisors for Investment to improve user experience and company performance. This study aims to examine customer behavior towards AI based features in mobile banking applications by using a UTAUT (Unified Theory of Acceptance and Use of Technology) model with data collected from 305 respondents, gathered using a quantitative method-based questionnaire that was distributed through social media platforms. The findings indicate that Performance Expectancy, Social Influence, and Trust have a positive and significant influence on Behavioral Intention, while Financial Risk has a negative and significant influence on Behavioral Intention, Meanwhile, Effort Expectancy, Financial Knowledge, and Financial Efficacy do not significantly influence Behavioral Intention. Furthermore, User Behavior is influenced by Behavioral Intention and Facilitating Condition indicating that the user's adoption of AI-based features in mobile banking is driven more by Performance Expectancy, Social Influence, Trust, Financial Risk, Behavioral Intention, and Facilitating Condition than by Effort Expectancy, Financial Knowledge, and Financial Efficacy. This study primarily consists of digitally literate respondents recruited through various social media platforms, therefore these findings should be interpreted within the context of the sample.

Keywords: Artificial Intelligence, Financial Technology, Mobile Banking, User Behavior, Utaut Model.

1. Introduction

The integration of Industry 4.0 technologies has become a cornerstone for organizational success, particularly in advancing sustainable financial operations and improving resource efficiency through Artificial Intelligence (AI) (Kumar *et al.,* 2024), (Mei *et al.,* 2024). The financial landscape in Indonesia shows that mobile banking providers prioritize increasing the usage of AI-based features to build better system comprehension, reasoning, and automated decision-making (Lim *et al.,* 2025). According to McKinsey & Company's 2023 survey, global trends and generative AI are aligned and have been used to forecast nearly double the banking industry's revenue growth from 2.8% to 4.7%; this result outperforms sectors like pharmaceuticals and telecommunications.

Despite the rapid growth of technology, user adoption behavior remains complex. Earlier generations helped establish the foundation for digital adoption (Ikhsan *et al.,* 2024), while the current market is influenced by Gen Z and university students who have grown up in a highly digital environment (Akhtar *et al.,* 2024), (Szymkowiak *et al.,* 2021). As these users begin to engage more actively, an important research gap emerges regarding how these digitally native users balance technological confidence with financial literacy when adopting AI-based banking features. While previous studies have examined general technology acceptance, this study focuses on examining the role of Financial Knowledge and Financial Efficacy within the UTAUT framework in the Indonesian mobile banking context. Therefore, this study seeks to fill this gap by examining the factors that influence AI adoption in mobile banking and connecting users' perception with their financial behavior.

As AI technologies continue to innovate, several industries such as the Banking Sector have leveraged AI to support sustainable development through innovative solutions enhancing both economic and environmental benefits

(Mei *et al.,* 2024). As an example, several Banks in Indonesia have implemented AI to give users a better offer of products & services on their mobile banking app. These are a few examples of how AI is implemented, as there are plenty more types of AI technologies. User experience, accuracy, and system efficiency are improved without human involvement (Ali *et al.,* 2025). This study focuses primarily on AI Features in mobile banking, defined as functionalities that use machine learning, predictive analytics, and natural language processing to deliver an adaptive and more accurate result. These include AI Chatbots for Customer Service, AI-Based Personal Financial Assistant, AI Credit Scoring and Loan Approval, and Robo Advisors for Investment. AI-enhanced security features such as AI Security Systems are included only insofar as they rely on intelligent algorithms. Unlike traditional mobile banking, AI-based features change the role of the system from a passive tool into a more active decision-support mechanism. This creates a different user experience as users decide whether they can trust the system's recommendations and predictive analysis.

In response, studies regarding customer behavior are important to give a better understanding of the customer's point of view. Despite thereof, limited studies investigate customer behavior toward a broad set of AI based features implemented on mobile banking. Unlike existing studies which focus primarily on mobile banking services and behavioral intentions individually, this research focuses on real usage behavior of Indonesians, supported with a large sample size, in the context of Artificial Intelligence. Furthermore, studies often rely on standard UTAUT and do not include variables of financial risk, financial knowledge, financial efficacy, and trust in AI altogether in Indonesia. This current study overcomes gaps found in other literature by incorporating such variables on standard UTAUT and investigating a broad set of AI based features.

This study is organized as the following: Section 1 begins with the introduction of the topic, Section 2 highlights the literature review and hypothesis development where the hypotheses are outlined, the methodology is outlined in Section 3, research findings and results are presented in Section 4, and finally the conclusions, theoretical implications, and limitations of this study are presented in Section 5.

2. Literature Review and Hypotheses Developments

2.1. The Evolution of AI in the Financial Landscape

The growth of Artificial Intelligence (AI) has fueled the growth of Industry 4.0, creating a major transformation in the financial sector that moves beyond basic automation toward greater operational efficiency and sustainable business practices (Mei *et al.,* 2024; Kumar *et al.,* 2024). The significant advancement of modern banking services has been boosted by the recent development of machine learning. Despite the advancement, machine-based problem solving can be traced back to the mid-twentieth century (Byambaa *et al.,* 2025; Ali *et al.,* 2025). The industry is shifting from traditional fintech services to AI-based solutions which offer accuracy, faster processes, and more personalized user experiences (Tyagi *et al.,* 2025; Sheth *et al.,* 2022).

In this era, technological progress also creates a paradox where innovation must be aligned with the variables most important for users. While service providers focus on reducing transaction risks, users remain cautious of the large amount of data required by AI systems, specifically regarding security threats and privacy violations (Ikhsan *et al.,* 2024; Sharma *et al.,* 2025). Therefore, technological advancement and the ability to combine perceived usefulness with a robust foundation of trust that reflects customer expectations are the factors which determine the success of modern banking (Ikhsan *et al.,* 2024).

2.2. Theoretical Framework and Hypotheses

This study develops a conceptual framework and hypotheses that systematically analyze the core UTAUT determinants, customer perspectives on risk, the mechanisms of trust-building, and the individual competencies and infrastructure available to the user (Figure 1). Through this integrated approach, we examine the specific variables influencing the adoption of AI-based features within digital banking. These hypotheses are tested using a quantitative questionnaire-based methodology, and the detailed findings regarding each variable are presented as follows.

2.2.1. UTAUT Core Determinants

The Unified Theory of Acceptance and Use of Technology (UTAUT) remains a comprehensive framework for analyzing consumer adoption, yet current studies suggest its core variables need adjustment to fit into AI-specific contexts (Sharma *et al.,* 2025). Within this study, Performance Expectancy (PE) and Effort Expectancy (EE) represent users' evaluation of the benefits associated with AI-based mobile banking features. PE refers to the belief that AI will help to improve financial management (Mei *et al.,* 2024), while EE claims that a higher willingness to adopt is only possible when the system is perceived as user friendly and easy to use (Mei *et al.,* 2024; Byambaa *et al.,* 2025). Moreover, Social Influence (SI) increases the adoption rates through interpersonal recommendation (word-of-mouth), specially in sustainable banking where subjective norms promote AI acceptance (Mei *et al.,* 2024; Ikhsan *et al.,* 2024). All variables contribute to shape Behavioral Intention (BI), which measures the user's willingness to utilize AI-based features in the future. With the growing looks on the user-friendliness and environmental impact (Shahzad *et al.,* 2022; Mei *et al.,* 2024), BI serves as the main driver to increase an individual's willingness to adopt the technology.

H1: Behavioral Intention (BI) has a positive influence on User Behavior (UB).

H2: Performance Expectancy (PE) positively influences Behavioral Intention (BI).

H3: Effort Expectancy (EE) positively influences Behavioral Intention (BI).

H4: Social Influence (SI) positively influences Behavioral Intention (BI).

2.2.2. Risk and Trust Mechanisms

As AI becomes increasingly integrated into banking services, perceived usefulness is not only the factor that shaped user adoption but also by concerns related to Financial Risk (FR). Financial risk is defined as the possibility of financial loss that may occur during a financial transaction, which can increase users' fragility (Ali *et al.,* 2025; Zhao & Khaliq, 2024). Users' may become less willing to adopt AI-based features when users perceive higher risks such as potential financial losses or system errors (Zhao *et al.,* 2024). To mitigate this, Trust (T) becomes an important factor in reducing users' concerns as it is closely related to ethical considerations such as data protection of user information and transparency (Byambaa *et al.,* 2025; Mei *et al.,* 2024). When financial institutions such as banks are able to address these concerns, they can strengthen users' confidence in AI-based banking systems and reduce perceived risk. Users are not only evaluating ease of use but also assessing whether they can trust the automated financial decisions.

H5: Financial Risk (FR) negatively influences Behavioral Intention (BI).

H8: Trust (T) positively influences Behavioral Intention (BI).

2.2.3. Individual Competence and Supporting Infrastructure

A significant gap in standard adoption models is the role of individual capability. This study extends the UTAUT framework by incorporating Financial Knowledge (FK) and Financial Efficacy (FE). While higher levels of FK enable more competent management of digital platforms (Akhtar *et al.,* 2024), AI uniquely functions as an automated tutor for users with lower educational backgrounds by simplifying complex technical advice (Ali *et al.,* 2025). Complementing this, FE determines whether a user feels capable of effectively controlling their financial outcomes (Sharma *et al.,* 2025). Finally, these individual competencies must be supported by Facilitating Conditions (FC). FC provides the constructive framework in which existing infrastructure aligns with the specialized technical requirements of AI (Mei *et al.,* 2024). In the banking context, organizations must implement these supporting factors to help translate user intention into User Behavior (UB). Unlike purely perceptual factors, facilitating conditions often directly dictate the final usage decision (Lopes *et al.,* 2025; Lim *et al.,* 2025).

H6: Financial Knowledge (FK) positively influences Behavioral Intention (BI).

H7: Financial Efficacy (FE) positively influences Behavioral Intention (BI).

H9: Facilitating Condition (FC) positively influences User Behavior (UB).

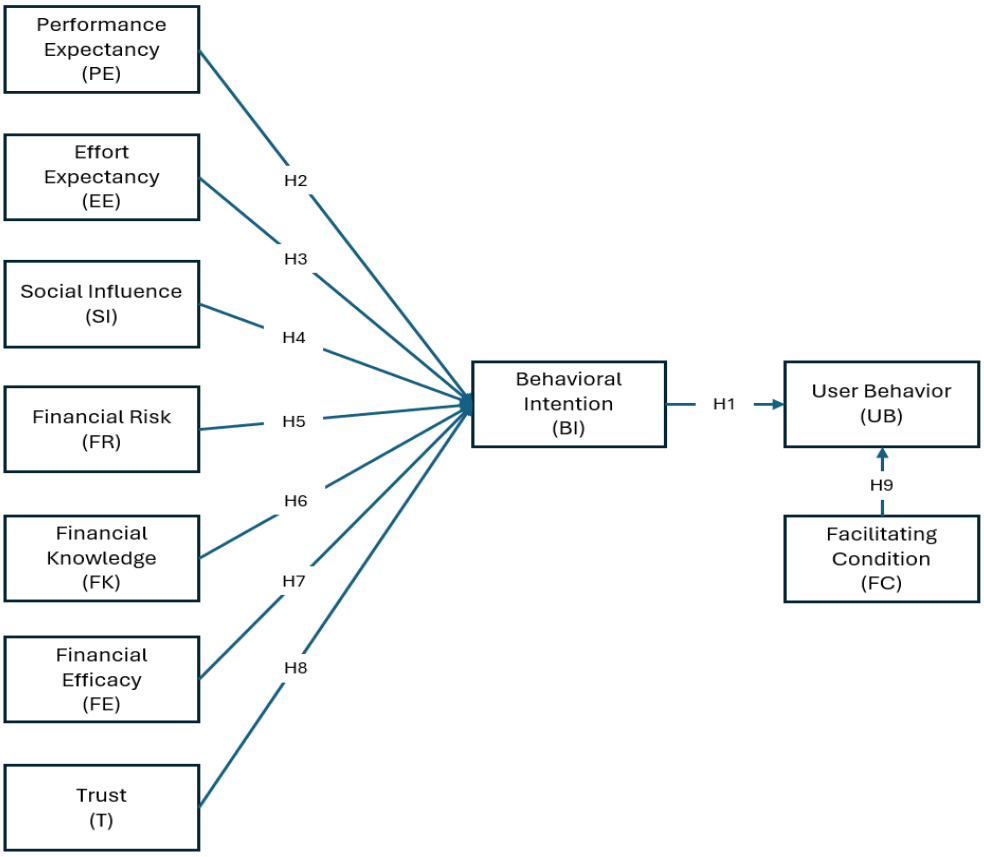

Figure 1. Conceptual Model provides a brief hypothesis provided in this study.

3. Methodology

3.1. Data Collection

Data were collected using a quantitative questionnaire-based method distributed through various social media platforms such as Instagram, Telegram, WhatsApp, and Line. This questionnaire used a five-point Likert Scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), allowing respondents to share their perception and satisfaction. Respondents in this research went through several screening questions that were used to filter out untargeted respondents with "How frequently do you use AI features?" which automatically directs the respondents to the end if "have never used" was chosen, 3 respondents were excluded. The process of data collection took around 3 weeks. A total of 305 responses were collected, of which 302 respondents were categorized as eligible and relevant to be analyzed for this study. Based on the PLS-SEM 10-time rule, a minimum of 80 observations (calculated by multiplying 10 to the eight structural paths pointing to Behavioral Intention) are needed for our model, therefore our sample size is adequate. Eligibility is determined based on whether the respondents have used AI features in mobile banking apps. A pilot questionnaire involving 30 respondents was conducted prior to the actual survey to ensure clarity, relevance, and preliminary reliability of the questionnaire items. The purpose of the pilot test was to ensure that the item wording was understandable and the format was easy for respondents to follow. Furthermore, the Preliminary reliability was also examined using Cronbach's Alpha to ensure internal consistency among the items within each construct. There were no major issues identified during the pilot test, therefore the questionnaire was appropriate for distribution in the main survey.

Since the questionnaire was distributed through social media platforms, the sampling approach may introduce a degree of sampling bias. Respondents are more likely to be familiar with mobile applications therefore the sample may overrepresent digital literate and underrepresent mobile banking users with lower digital exposure. Hence, this should be considered when interpreting the findings, particularly the insignificant effects of effort expectancy, financial knowledge, and financial efficacy on behavioral intention.

The questionnaire items were developed by the authors by referring to construct definitions and findings from previous studies. The items were not taken directly from existing measurement scales, but were designed based

on relevant literature and adjusted to the context of AI-based features in mobile banking applications**.** Appendix A shows the detailed questionnaire items, literature basis, and item development information.

3.2 Ethical Considerations

This study is based on the ethical principles for online survey research. Prior to completing the questionnaire, respondents were informed about the purpose of the study and the identity of the researchers, and the academic purpose of the questionnaire prior to filling the survey. The questionnaire invitation also explained that the responses would be treated confidentially and would not reveal respondents' personal identities directly. Respondents were provided the researchers' contact information to ask questions. Participation was voluntary, and respondents who continued to complete the questionnaire were considered to have provided informed consent to participate. All collected data were analyzed collectively to protect respondents' privacy and confidentiality.

3.3. Respondents' Demographic Profile

The secrecy of participants during an online survey must feel protected and anonymous in order to give honest and reliable responses.

Table 1. Demographic profile of the respondents

Variable	Description	Frequency	Percentage (%)
Gender	Male	155	51%
	Female	147	49%
Year Born	1981 – 1984	2	1%
	1985 - 1988	4	1%
	1989 – 1992	8	3%
	1993 – 1996	19	6%
	1997 – 2000	19	6%
	2001 – 2004	180	60%
	2005 - 2008	70	23%
Education	Highschool	63	21%
	Diploma	4	1%
	Bachelors	221	73%
	Masters	14	5%
	Doctorate	0	0%
Occupation	Unemployed	146	48%
	Private sector employee	82	27%
	Civil employee	15	5%
	Entrepreneur	35	12%
	Others	24	8%
Region	Jakarta	136	45%
	Bogor	10	3%
	Depok	21	7%
	Bekasi	16	5%
	Tangerang	99	33%
	Others	20	7%
Income Level	0 – 10 million/month	228	75%
	11 – 30 million/month	57	19%
	31 – 50 million/month	17	6%

They should never worry that their demographic details and personal details will be exposed (Akhtar *et al.,* 2024), ((Murdoch *et al.,* 2014, Mueller *et al.,* 2014)). Table 1 shows a diverse sample of demographic characters: Gender (51% of the respondents were Male and 49% were Female), Year Born (23% respondents were born between the year 2005-2008, majority were born between the years of 2001-2004, and the rest are diverse as shown

on the Table 1), Education (The majority of the respondents have a Bachelors and are still doing their Bachelors, 73%, 21% for Highschool, 5% for Masters, and 1% for Diploma), Occupation (Unemployed as much as 48%, Private sector employee 27%, Civil employee 5%, Entrepreneur 12%, and Others 8%), Region (Jakarta as much as 45%, Bogor 3%, Depok 7%, Bekasi 5%, Tangerang 33%, and Others 7%), and Income Level (0 - 10 million/month as much as 75%, 11 - 30 million/month 19%, and 31 - 50 million/month 6%). Table 1 shows that the majority of our respondents are born between the years of 2001-2004, currently pursuing or have a bachelor's degree, have not worked, live in Jakarta, and earn between 0-10 million/month. Therefore, our research does not represent the general Indonesian banking-user.

3.4. Data Analysis

The analysis was carried out in two stages. First, the measurement model was analyzed to assess the constructs' external validity and reliability. After that, the structural model was examined to test the hypothesized relationships among variables, therefore providing a comprehensive assessment of our overall model (Mei *et al.,* 2024), (Hair *et al,* 2021). The data were analyzed using Smart PLS 4.0 using Cronbach's Alpha for construct reliability testing because it measures internal consistency reliability, whereas convergent validity was analyzed using Average Variance Extracted (AVE) because it shows the validity of each construct and measures what it is supposed to measure. To address potential common method bias, this study conducted a full collinearity assessment. Furthermore, HTMT was chosen for discriminant validity because it provides statistical detection of discriminant validity problems.

Table 2: Measurement Model

Latent Variables	Indicators	Loadings	Cronbach's Alpha	AVE	CR
Behavioral Intention	BI1	0,751	0,874	0,615	0,905
	BI2	0,841			
	BI3	0,734			
	BI4	0,738			
	BI5	0,842			
	BI6	0,792			
Performance Expectancy	PE1	0,832	0,897	0,708	0,924
	PE2	0,866			
	PE3	0,839			
	PE4	0,833			
	PE5	0,836			
Effort Expectancy	EE1	0,711	0,830	0,539	0,875
	EE2	0,761			
	EE3	0,705			
	EE4	0,749			
	EE5	0,715			
	EE6	0,763			
Social Influence	SI1	0,908	0,932	0,830	0,951
	SI2	0,918			
	SI3	0,927			
	SI4	0,891			
Financial Risk	FR1	0,806	0,897	0,707	0,923
	FR2	0,881			
	FR3	0,889			
	FR4	0,812			
	FR5	0,811			
Financial Knowledge	FK1	0,769	0,804	0,628	0,871
	FK2	0,778			
	FK3	0,787			

	FK4	0,835			
Financial Efficacy	FE1	0,706	0,714	0,618	0,828
	FE2	0,772			
	FE3	0,871			
Trust	T1	0,837	0,854	0,696	0,901
	T2	0,838			
	T3	0,859			
	T4	0,801			
Facilitating Condition	FC1	0,799	0,734	0,654	0,850
	FC2	0,760			
	FC3	0,863			
User Behavior	UB1	0,837	0,867	0,653	0,904
	UB2	0,841			
	UB3	0,752			
	UB4	0,796			
	UB5	0,810			

Abbreviations: AVE: Average Variance Extracted; CR: Composite Reliability

In the reliability indicator, the size of outer loadings was evaluated with the recommended threshold of 0.70 as it indicates that an item shares more variance with its construct rather than with an error (Mei *et al.,* 2024), (Hair, J.F., *et al.,* 2021). Table 2 shows that all item loadings exceed the threshold, demonstrating strong indicator reliability. Furthermore, Cronbach's Alpha and Composite Reliability (CR) was used to measure the internal consistency. The Cronbach's Alpha indicated that all the values range from 0.714 to 0.932, exceeding the threshold which indicates that items consistently measure the same latent variable. CR values range from 0.828-0.951, which is considered a strong internal consistency. The Average Variance Extracted (AVE) has a threshold of 0.50 which indicates that more than half of the variance of the items is captured by the construct, Table 2 shows that the values range from 0.539 to 0.830.

Table 3. Discriminant Validity

	BI	EE	FC	FE	FK	FR	PE	SI	T	UB
BI										
EE	0,762									
FC	0,639	0,781								
FE	0,567	0,707	0,774							
FK	0,546	0,659	0,760	0,823						
FR	0,191	0,082	0,095	0,181	0,090					
PE	0,872	0,815	0,703	0,552	0,500	0,124				
SI	0,679	0,644	0,533	0,538	0,510	0,081	0,564			
T	0,744	0,686	0,820	0,686	0,627	0,122	0,687	0,639		
UB	0,771	0,691	0,823	0,664	0,663	0,125	0,705	0,738	0,859	

Abbreviations: BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; FE: Financial Efficacy; FK: Financial Knowledge; FR: Financial Risk; PE: Performance Expectancy; SI: Social Influence; T: Trust; UB: User Behavior

Table 3 shows the discriminant validity which was evaluated using Heterotrait-Monotrait Ratio (HTMT). Most of the HTMT values shown were below the recommended threshold of 0.85 (strict criterion), suggesting that most constructs are empirically distinct from one another and measure unique conceptual domains. However, Behavioral Intention – Performance Expectancy (0.872) and Trust – User Behavior (0.859) exceeded the threshold of 0.85. Nevertheless, all values are below 0.90 (lenient criterion) (Mei *et al.,* 2024), (Hair *et al.,* 2021). Therefore, the relatively high HTMT values indicate these pairs should be interpreted with caution.

4. Findings and Discussions

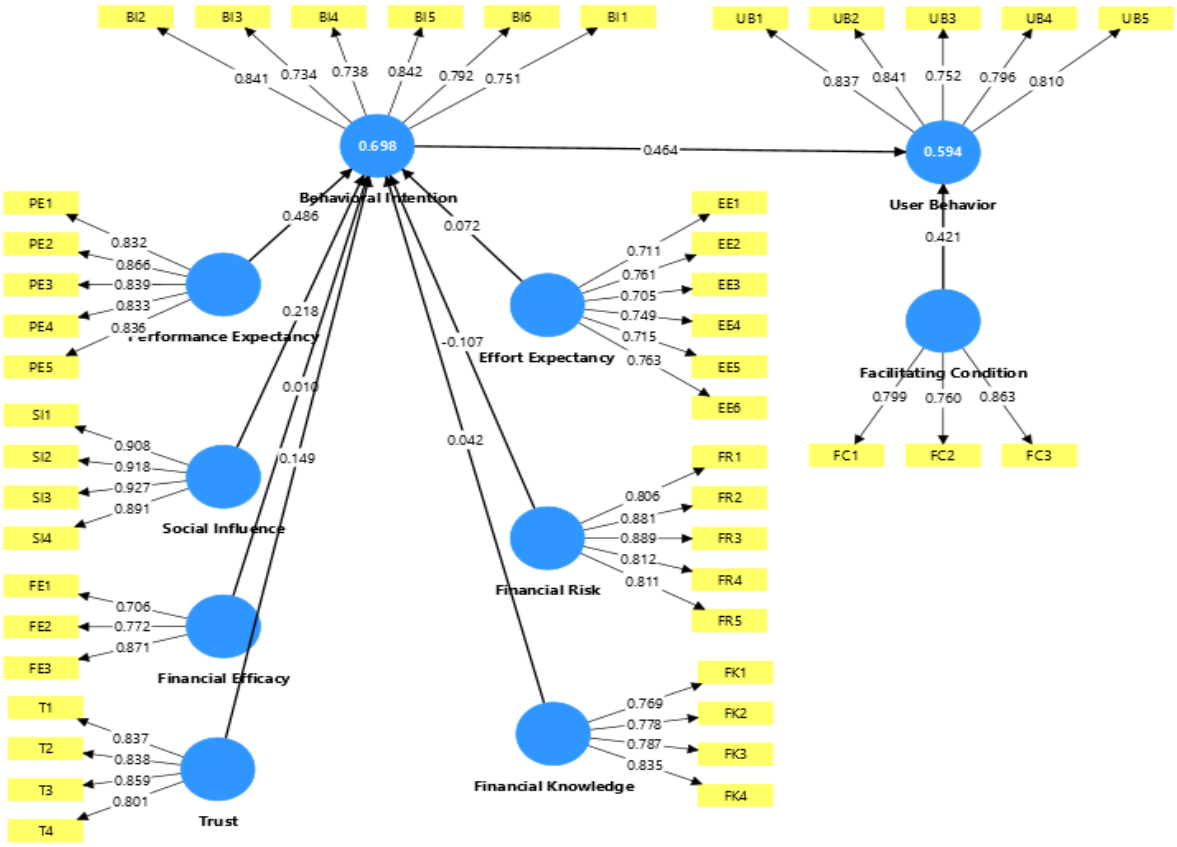

Figure 2. Structural Model.

Table 4. Structural Model Evaluation

Endogenous Construct	R^2
Behavioral Intention	0.698
User Behavior	0.594

Table 4 shows the explanatory power of the structural model was assessed using the coefficient of determination (R^2). Table 4 shows that the value for Behavioral intention is 0.698, indicating that Performance Expectancy, Effort Expectancy, Social Influence, Financial Risk, Financial Knowledge, Financial Efficacy, and Trust explain 69,8% of the variance in Behavioral Intention. This indicates that the model has a relatively strong ability to explain users' intention to adopt AI-based features in mobile banking applications. Meanwhile, the R^2 value for User Behavior is 0.594 indicating that Behavioral Intention and Facilitating Condition explain 59.4% of the variance in User Behavior. This indicates that Behavioral Intention and Facilitating Condition explain a moderate proportion of users' actual behavior. These findings on Table 4 suggest that the model has moderate explanatory power in explaining both the intention and actual usage of AI-based features in mobile banking.

Table 5 summarizes the structural model which was assessed for potential multicollinearity among the variables using the inner Variance Inflation Factor (VIF). As shown in the table, all relationships result in VIF values ranging from 1.050 to 2.590 which are below 5. According to (Akhtar *et al.*, 2024), VIF values below 5 indicate that multicollinearity is not a major concern.

The structural model was also evaluated using effect size (f^2) to determine the relative contribution of each exogenous construct to the explanatory power of the endogenous construct. The f^2 value shows the change in R^2 when a specific predictor is removed from the model. Table 6 shows that f^2 results indicate that Behavioral Intention has a large effect on User Behavior (f^2 = 0.389), this means that users actual usage of AI-based features in mobile

banking is strongly associated with their intention to adopt them. Facilitating Condition has a medium effect on User Behavior (f^2 = 0.320), the medium effect means users are more likely to use AI-based mobile banking features when they have necessary support such as internet access.

Table 5. Collinearity Assessment

Relationship	VIF (Variance Inflation Factor)	Decision
BI → UB	1.363	No critical collinearity
FC → UB	1.363	No critical collinearity
EE → BI	2.590	No critical collinearity
FE → BI	2.066	No critical collinearity
FK → BI	1.872	No critical collinearity
FR → BI	1.050	No critical collinearity
PE → BI	2.288	No critical collinearity
SI → BI	1.749	No critical collinearity
T → BI	2.151	No critical collinearity

Abbreviations: BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; FE: Financial Efficacy; FK: Financial Knowledge; FR: Financial Risk; PE: Performance Expectancy; SI: Social Influence; T: Trust; UB: User Behavior

Table 6. Effect Size

Relationship	f^2	Effect size
BI → UB	0.389	Large
FC → UB	0.320	Medium
EE → BI	0.007	Negligible
FE → BI	0.000	Negligible
FK → BI	0.003	Negligible
FR → BI	0.036	Small
PE → BI	0.342	Medium
SI → BI	0.090	Small
T → BI	0.034	Small

Abbreviations: BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; FE: Financial Efficacy; FK: Financial Knowledge; FR: Financial Risk; PE: Performance Expectancy; SI: Social Influence; T: Trust; UB: User Behavior

Table 7. Predictive relevance

Endogenous Construct	Q^2	RMSE	MAE
Behavioral Intention	0.675	0.576	0.421
User Behavior	0.601	0.637	0.506

Abbreviations: RMSE: Root Mean Square Error; MAE: Mean Absolute Error

Table 8. Path coefficients

Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-Statistics	P Values
BI → UB	0.464	0.463	0.050	9.246	0.000
EE → BI	0.072	0.073	0.058	1.254	0.210
FC → UB	0.421	0.423	0.046	9.109	0.000
FE →BI	0.010	0.010	0.053	0.181	0.857
FK → BI	0.042	0.042	0.052	0.812	0.417
FR → BI	-0.107	-0.110	0.031	3.445	0.001
PE → BI	0.486	0.486	0.055	8.795	0.000
SI → BI	0.218	0.217	0.056	3.866	0.000
T → BI	0.149	0.149	0.054	2.731	0.006

Abbreviations: BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; FE: Financial Efficacy; FK: Financial Knowledge; FR: Financial Risk; PE: Performance Expectancy; SI: Social Influence; T: Trust; UB: User Behavior

Table 7 results indicate that the model has predictive relevance for Behavioral Intention and User Behavior. The Q^2 predict value for Behavioral Intention is 0.675, while User Behavior is 0.601. This indicates that the proposed model also has the ability to predict these constructs as the model demonstrates predictive relevance for both endogenous constructs. This is determined since both values are greater than zero. The RMSE and MAE values show the level of prediction error for each construct, where lower values indicate smaller prediction errors.

Table 8 summarizes the path coefficients and hypothesis testing results of the relationships between the independent variables and dependent variables of behavioral intention, and user behavior. The results were generated through bootstrapping, as shown in Figure 2. The path coefficient indicates the direction and strength of each relationship, the standard deviation represents the variability of the estimated coefficients across bootstrap samples. Furthermore, the T-statistics and P-Values are used to assess the statistical significance of each relationship. T-statistics greater than 1.96 and a p-value below 0.05 indicate that the relationship is considered statistically significant at the 5% level. However, the strength and direction of the relationship are interpreted based on the path coefficient, not the t-statistic. Table 8 shows 3 insignificant effects of effort expectancy, financial knowledge, and financial efficacy to behavioral intention which is indicated on having a p-value > 0.05 therefore does not significantly influence behavioral intention. The insignificant effect of effort expectancy on behavioral intention should be interpreted in relation to the sample's characteristics. Respondents may already perceive mobile banking applications and AI-driven features as easy to use as they were recruited through various social media platforms. Therefore, effort expectancy may not stand out as a significant differentiating factor within this group. However, this result should not be generalized to all banking users, especially older groups with lower digital literacy level.

The findings show that users who actually use AI-based features are users with a stronger intention to adopt AI-based features in mobile banking. This is indicated by the positive and significant effect of Behavioral Intention on User Behavior ($\beta = 0.464$, $t = 9.246$, $p < 0.001$). Therefore, Behavioral Intention is an important predictor of User Behavior as it explains the actual user behavior in the context of adoption.

Furthermore, findings show that users are more likely to adopt AI-based features in mobile banking apps primarily because they believe that the features will be useful for their banking experience and financial activities. This is indicated by performance expectancy exhibiting the strongest positive and significant effect among others ($\beta = 0.486$, $T = 8.795$, $p < 0.001$). This result supports the findings of (Rahman *et al.,* 2023), who reported that perceived usefulness, like performance expectancy, significantly influences the users' intention to adopt AI in the banking industry, suggesting that it remains a dominant factor influencing the adoption of technology. This is in line

with Lim et al (Lim *et al.,* 2025) study which states that Perceived Usefulness or Performance Expectancy has a significant positive effect on users' adoption intention toward AI in Banking.

Our findings also show that encouragement from family, friends, and peers can increase the users' intention to use AI features, indicated by Social Influence having a positive and significant effect on Behavioral Intention (β = 0.218, T = 3.866, p < 0.001). Patel and Patel (Patel & Patel, 2018), as cited in Lim et al. (Lim *et al.,* 2025) noted that social influence or subjective norms is an important factor in technology adoption. People's intention to use technology is also influenced by support from people around them. According to Lopes et al. (Lopes *et al.,* 2025), Social influence is one of the determining factors in users' intention to adopt a technology and motivate users to accept AI adoption especially if users already feel satisfied by using traditional services.

Trust has a positive and significant effect on Behavioral Intention (β = 0.149, T = 2.731, p = 0.006). This result indicates that users are more likely to adopt AI-based features in mobile banking if they have trust in the bank and its AI system, therefore financial institutions such as banks need to make users feel safe and secure during doing transactions or when using newly developed technological features. This finding is consistent with previous studies which showed that trust was found to have a significant and positive factor on usage intention, highlighting its important role in strengthening users' intention and perceived risk to adopt new developed technologies (Tyagi & Bhatt, 2025), (Appiah & Agblewornu, 2025).

A higher financial risk is also shown to lower the intention to use AI features (β = -0.107, t = 3.445, p = 0.001). Several factors of wrong AI decisions and financial loss reduce willingness to use AI features. Risk becomes a factor which consumers tend to weigh more heavily than expected gains during decision making, therefore it plays an important factor when evaluating fintech services (Zhao & Khaliq., 2024). Therefore, banks need to actively monitor suspicious risks that might occur in new features. McKinsey's latest research found that an evolution in risk mitigation capabilities with Gen AI are needed as it can automatically update customer risk ratings in response to real time changes in knowing your customer (KYC) information through transaction patterns based on customer activities.

Findings found that effort expectancy does not have a significant effect on Behavioral Intention (β = 0.072, T = 1.254, p = 0.210) within this sample. This might be because many respondents were recruited through social media platforms, therefore they may be digitally familiar. This finding is consistent with Lim et al (Lim *et al.,* 2025) in which the study found that ease of use of AI in banking services is not a concern for Gen Z users who are digitally literate. Therefore, this finding should not be generalized to all banking users, particularly older users with lower levels of digital literacy.

Furthermore, findings found that facilitating conditions have a positive and significant effect on User Behavior (β = 0.421, t = 9.109, p < 0.001). This suggests that users are more likely to use AI-based features in mobile banking when they believe that the necessary resources and infrastructure, such as stable internet connection, smartphones, and system compatibility, are available. These facilitating conditions may increase users' confidence and readiness to use AI-based features because they have the necessary support in operating the technology. This finding positions Facilitating Conditions as a direct predictor of User Behavior, therefore it is consistent with the original UTAUT framework. User Behavior in this study is operationalized as self-reported frequency and consistency of AI feature usage.

Financial knowledge does not have a significant effect on Behavioral Intention (β = 0.042, T = 0.812, p = 0.417). This suggests that users' level of financial knowledge is not a major factor in determining their intention to use AI based features. AI-based features are designed to simplify financial activities allowing, easing users with different financial literacy levels. Therefore, performance expectancy, trust, financial risk, and social influence influence users' intention to adopt these features more than Financial Knowledge.

Lastly, financial efficacy does not significantly influence behavioral intention (β = 0.010, T = 0.181, p = 0.857). Within this sample, these findings suggest that users' confidence in managing their personal finance does not play a major role determining their intention to adopt AI-based features in mobile banking. AI systems are designed to simplify complex financial activities through automated analytics. This indicates that performance expectancy, trust, financial risk, and social influence influence users' intention to adopt AI-based features more than Financial Efficacy.

5. Conclusion

The study examined customer behavior toward AI-based features in mobile banking applications by extending the UTAUT framework with Financial Risk, Financial Knowledge, Financial Efficacy, and Trust. Based on the 302 valid responses, the findings show that Performance Expectancy, Social Influence, and Trust positively and significantly influence Behavioral Intention, while Financial Risk has negative and significant effect on Behavioral Intention. The findings also show that Behavioral Intention and Facilitating Condition positively and significantly influence User Behavior. Meanwhile, Effort Expectancy, Financial Knowledge, and Financial Efficacy do not significantly affect Behavioral Intention in this sample. Overall, the findings indicate that the adoption of AI-based mobile banking features is more strongly associated with Performance Expectancy, Social Influence, Trust, and Financial Risk than with Effort Expectancy or users' financial capability. This suggests that users' intention to adopt AI-based mobile banking features is shaped mainly by Performance Expectancy, Social Influence, Trust, and Financial Risk while actual user behavior is influenced by both intention and facilitating conditions. However, these findings should be interpreted within the context of the sample, which mainly consists of younger and digitally familiar respondents recruited through social media platforms.

5.1 Theoretical Implications

The development of UTAUT was originally in the context of traditional information systems, this study extends the applicability to AI based features in mobile banking. This study strengthens the technology adoption theory, particularly within the context of AI-based mobile banking, by confirming that the central role of performance expectancy as the strongest determinant and the most influential in predicting behavioral intention aligns with UTAUT. This suggests that users' motivation to adopt is prioritized by functional benefits and performance enhancement. Second, the significant roles of social influence, trust, and financial risk highlight the importance of social context and risk-related factors in shaping the intention of users in adopting AI indicating that despite technological developments of financial technologies, users still consider fear of financial loss as a strong barrier therefore data protection and system integrity plays a crucial role in AI environments. Furthermore, AI adoption also depends on transparency and reliability of algorithmic decisions. Algorithmic decisions refer to the recommendations generated automatically by the AI. In the context of mobile banking, the financial and behavioral data are processed and gone through predictive modelling therefore the decisions are not made by human employees. Third, the insignificant roles of effort expectancy, financial knowledge, and financial efficacy show a shift in relevancy. In the context of this specific study, traditional predictors such as effort expectancy and financial knowledge did not show a significant impact. This suggests that for a digitally literate sample, these factors might be perceived as baseline requirements rather than active motivators. These findings show that there is a shift in the determinants, moving towards perception of value and safety alongside the credibility of the bank.

5.2 Managerial Implications

The findings provide several insights for the Indonesian banking industry and financial technology developers. First, since performance expectancy is the primary and also the strongest driver of behavioral intention, banks should pivot their strategy from only focusing on user interface to strengthening the function value and personalization of the features. For example, banks can prioritize developing tools that provide clear and tangible benefits for users' financial activities such as AI-based personal financial assistants, robo-advisors, and other financial recommendation tools. Since effort expectancy was not significant within this sample, banks should ensure AI features are relevant and valuable in helping users. Furthermore, banks should strengthen transparency in the use of AI-based systems, this is given the importance of Trust and the negative effect of Financial Risk. Banks should ensure the reliability of algorithmic decisions so credit related decisions are understandable and reliable to users. To build greater trust, banks should also clearly communicate how they detect fraud in real time, manage data, and protect customer data according to their users' privacy guidelines.

Finally, Facilitating conditions should be strengthened by banks, as they have direct influence on User Behavior. Managerial efforts should focus on ensuring that AI-based features are accessible across devices, supported by clear user guidance, and able to operate under different environments with different internet conditions. By

combining these technical supports, banks can better encourage users to shift from intention to continued use of AI-based features on mobile banking applications.

5.3 Limitations

This study is not without limitations as there are several that should be acknowledged. First, this research was created using data that was collected using a self-reported questionnaire which may be subjected to biases such as respondents answering based on what they think are socially acceptable, respondents also may have misunderstandings or memory errors in survey items. Therefore, this may not fully reflect actual behavior in the real world.

Second, the demographic may be influenced with biases as the majority of respondents were Gen Zs which are more frequently exposed to AI-driven technologies and are familiar with digital ecosystems. The non-significant effects of effort expectancy, financial knowledge, and financial efficacy might be the result of the demographic being mostly Gen Zs or digital literate users. Older groups or users with lower digital literacy may experience different adoption barriers that are not captured in this study which means that the results cannot be assumed to represent the entire banking population. In addition, the findings should be viewed as sample-contingent rather than as general evidence that effort expectancy and facilitating conditions are no longer important in AI-based mobile banking adoption.

Third, AI related attitudes can experience changes due to policy changes or improvement on their AI systems done by banks. The improvements in accuracy and transparency may affect the perception of how users evaluate over time. In terms of cross-sectional snapshot, respondents' perceptions are influenced by their level of exposure and existing AI features on mobile banking apps offered by banks. As users interact more with AI, their trust may increase and their perception of risk might decrease and variables that appear insignificant might become more or less relevant for users.

Finally, this theoretical model does not include factors that interact with core UTAUT constructs and shape adoption outcomes such as AI literacy, algorithmic transparency, cultural norms, or personal innovativeness. Therefore, future studies should expand and capture the absence of such variables to more accurately reflect the full complexity nature of AI adoption in mobile banking.

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Author Contributions

Tristandi Tobias: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. Stephen Cornelius Lay: Investigation, Methodology, Writing – original draft. Triasesiarta Nur: Supervision, Validation, Writing – review & editing, Project administration. All the authors read and approved the final version of the manuscript.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools (ChatGPT 5) was used only to improve language and readability of the manuscript. The authors take full responsibility for the content and accuracy of the manuscript.

Data Availability Statement

The anonymized primary dataset supporting the findings of this study is available from the corresponding author upon reasonable request.

Conflict of Interest

The authors have no conflicts of interest to declare. There is also no financial interest to report. The author certifies that the submission is original work and is not under review at any other publication.

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