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Research Article

An Application of the UTAUT Model to Investigate User Acceptance of Facial Recognition Technology in Mobile Banking: A Case Study from Thailand

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Abstract: This research examines the determinants affecting consumers' willingness to embrace facial recognition technology for mobile payments in Thailand. Utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT), the study incorporates eight fundamental constructs: Performance expectancy, effort expectancy, social influence, facilitating conditions, perceived ease of use, perceived usefulness, attitude toward use, and intention to utilize facial recognition. Furthermore, demographic moderators such as age, gender, and mobile experience were incorporated to investigate potential variations in user adoption behavior. 539 people who used mobile banking filled out a standardized questionnaire to provide us with the data we needed. Using PLS-SEM through SmartPLS 4.0, structural equation modeling showed that the model was both reliable and valid. The results indicate that most of the hypothesized paths are important, except for the direct effects of performance expectancy and facilitating conditions on intention. Only age had a partial effect as a moderator; the moderating effects of age on other paths, gender, and mobile experience were not significant. These findings offer lessons for banks, mobile service providers, and policymakers particularly the Bank of Thailand on enhancing the design, regulation, and user trust in biometric authentication systems by considering both technological and demographic factors.

Keywords: Face Detection, Face Recognition, Mobile Banking Payment, UTAUT, Smart PLS

Introduction

Information technology has grown quickly in the modern world and is now a part of everyone's daily life. At the same time, businesses have had to change their plans to meet customer needs, which has included making a wide range of goods and services quickly. This lowers costs and makes it easier to gain a competitive edge.

Thailand's financial transaction data has grown a lot since smartphones and the internet became popular. The Denso-Wave company first made QR code payments available in Japan in 1994. This may have helped the rise. State-level rules and incentives made it easier to create QR code systems that meet international standards. This made financial transactions and other business activities more efficient and easier to use. However, even with the security measures put in place for different payment methods, bad people still try to break into networks and steal users' personal information. Some bank customers may lose money because of this. As a result, the Bank of Thailand has made it a rule that all banks that offer mobile banking apps must ensure that transactions are as safe as possible while those apps are being used. Scammers have used these networks in the past to trick people into sending them money. According to rules set by the Bank of Thailand, users must prove their identity when they make transactions. This policy's goal is to keep an eye on and deal with problems related to fraud and deception that happen when people use deposit accounts or electronic accounts by requiring identity verification for every transaction.

The following types of transactions use mobile banking apps that need facial scanning to confirm identity:

(1) Transactions worth more than 50,000 Baht
(2) Daily transfers worth more than 200,000 Baht
(3) Changes to transfer limits

The Bank of Thailand says that all banks must start following these rules by June 2023. Face scanning isn't needed for transactions that are below these limits. Five years ago, a restaurant in Hangzhou, China, opened and started using facial scanning technology as a way to pay. This method quickly became popular and was seen as a cutting-edge way to do business in China's hospitality, dining, and retail sectors, like hotels, shopping malls, and self-serve convenience stores (Zhong et al., 2021). People are still using and accepting this technology today.

In various contexts, multiple empirical studies have utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine the adoption of mobile payments. For example, Abrahão et al. (2016) investigated Brazil's adoption of mobile payments, revealing that behavioral intention was affected by perceived risk, social influence, performance expectations, and effort expectations, but not by perceived cost. Likewise, Lian and Li (2021) examined continuance intention in Taiwan and discovered that various dimensions of trust substantially influenced users' readiness to persist in mobile payment adoption. Furthermore, studies in Southeast Asia, such as in Indonesia and Vietnam, have also applied technology acceptance models (e.g., TAM, UTAUT) to understand the adoption of e-payment systems and social media commerce, highlighting the role of perceived ease of use and perceived usefulness in influencing consumer behavioral intention in the region (Junadi and Sfenrianto, 2015; Wijaya et al., 2019).

While empirical studies on facial recognition adoption in Thailand remain rare, several recent investigations in the broader Southeast Asia and global contexts offer useful comparison points. (Guleria, 2024) presents global adoption trends for facial recognition and discusses key facilitators and barriers, supporting the view that technological, regulatory, and trust factors are central to adoption decisions. Lim et al. (2025) analyze the biometric data regimes in Southeast Asia, highlighting how legal and policy frameworks influence public trust and data sensitivity insights directly relevant to the Thai regulatory context. Meanwhile, Rahman et al. (2024) examines mobile banking adoption dynamics in Malaysia, offering behavioral parallels that may apply within Southeast Asian digital banking ecosystems. Furthermore, Zarco et al. (2024) provides a comprehensive review of biometric payment adoption in retail settings, suggesting cross-sectoral patterns in user acceptance that can inform financial service design. Together, these studies fortify the contextual foundation for this research and underscore the need to localize findings within Thailand’s unique regulatory, cultural, and technological landscape.

Despite the increasing global adoption of biometric technologies, there remains a notable research gap concerning the empirical testing of the UTAUT framework in biometric mobile banking, particularly within the Thai context. While earlier studies have explored mobile banking and QR code adoption, few have examined how traditional UTAUT constructs performance expectancy, effort expectancy, social influence, and facilitating conditionsmexplain users’ behavioral intentions toward facial recognition technology in financial transactions.

Recent research emphasizes that issues of trust, perceived risk, and privacy are critical to understanding user acceptance of biometric systems (Guleria, 2024; Lim et al., 2025; Zarco et al., 2024). However, these concerns are contextually shaped by national regulations such as Thailand’s Personal Data Protection Act (PDPA), which emphasizes the necessity of localized models of trust and data protection in digital finance.

Accordingly, this study aims to fill these gaps by empirically testing a UTAUT-based model of face detection adoption in mobile banking, incorporating age, gender, and mobile experience as moderating variables and situating the analysis within Thailand’s evolving regulatory and cultural landscape. This approach contributes to both theoretical advancement in biometric technology acceptance and practical implications for developing secure, user-centric, and privacy-compliant financial services in Thailand.

Theoretical Background and Hypothesis Development

This research employs the Unified Theory of Acceptance and Use of Technology (UTAUT) to elucidate various phenomena. This theory seeks to elucidate and forecast the adoption and utilization of new technology or alternative information systems by individuals, particularly within business contexts. It also looks at whether people will be open to new technologies (Venkatesh et al., 2003) in order to encourage the growth and use of technology in a variety of organizations. The UTAUT model is frequently extended (e.g., as UTAUT2) to consumer-based technology, which is highly relevant to mobile banking adoption, where constructs like hedonic motivation and price value are often incorporated, as seen in studies on mobile banking in India and other developing economies (Dhingra and Gupta, 2020; Madan and Yadav, 2016).

Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Condition

(FC) are the four main parts of the UTAUT theory. They are important factors in deciding how people use and adopt technology. At the same time, the way people use things and the environment that makes it easy for them to do so are closely linked. Gender, age, and experience are the three most important moderating variables that help link behavioral intention to behavior manifestation.

Intention to Use Face Detection

People want to use electronic payment technologies because they want to be able to pay for things online. There are many ways to pay for things right now, including credit cards, QR codes with bank apps, and electronic wallets, or e-wallets. The Bank of Thailand has a policy that says that transfers of 50,000 baht or more must use face scan verification. Starting on July 1, 2023, this rule will be in effect. If users haven't already done so with a face scan, they will need to use a bank app that lets them verify their identity digitally (National Digital ID; NDID) or go to a bank branch. When you ask for or use services from either a public or private organization, you can use NDID, a digital identity verification service.

Smartphones have changed the way people pay. Instead of cash, cards, or wallets, people now use passwords and linked electronic accounts to make purchases. But there are also risks that come with this change, like the possibility of password theft or breaches. Biometric technology is becoming more and more popular as a way to make sure payments are stable (Zhang, 2022).

Research has demonstrated that facial recognition technology possesses potential for facilitating secure authentication in the dynamic field of mobile banking (Patel et al., 2016). The integration of biometrics, such as facial recognition and eye-blink verification, has been shown to significantly enhance security and reduce fraud risk in cardless transactions, making it a critical area of research in financial technology (Beg et al., 2024). Nonetheless, challenges have been identified, including persistent validation issues and inconsistencies in facial captures (Fathy et al., 2015). In this context, face detection algorithms are examined, and the significance of resilient systems is highlighted (Kumar et al., 2019). So, even though face detection in mobile banking looks very promising, more research is needed to make sure the technology works and is used in Thailand, as well as to fix the problems that have been brought up.

Performance Expectancy

The performance expectancy is a way to measure how much people think electronic payment technologies are worth. This technology is based on the idea that it makes payments safer, faster, and more accurate, which makes them more efficient (Venkatesh et al., 2003). Mobile banking users can do their financial business whenever it's convenient for them, which makes them more productive overall because it's quick and flexible (Dhingra and Gupta, 2020).

Using the Unified Theory of Acceptance and Use of Technology (UTAUT) model, (Nan et al., 2022) examined the impact of performance expectancy on users' intentions to utilize Face Recognition Payment (FRP) in offline markets. The study mainly focuses on facial recognition for mobile payments, but it also gives useful information about how users think about security, ease of use, and trust, which are all important things to think about when trying to predict performance. The study also found that perceived risk, performance expectancy, effort expectancy, and social influence all had a big impact. One great thing about mobile banking is that it lets you do financial transactions anywhere, at any time, even when businesses are closed. In theory, this greater accessibility should make more people want to use it. When people think that mobile banking will make their lives better in a big way, they are more likely to use it as part of their daily routine (Abrahão et al., 2016). Therefore, it is thought that:

Hypothesis 1: The performance expectancy has a positive effect on:

a) Perceived ease of use
b) Perceived usefulness
c) Intention to use face detection for mobile payment

Effort Expectancy

The user's idea of how easy it is to learn and use an electronic payment method is called "effort expectation." It discusses the system's complexity, learning time, and technical requirements. Previous research indicates a positive correlation between technology adoption and effort expectancy. Users are more likely to use technology in their daily lives if they think it is simple to use (Abrahão et al., 2016; Venkatesh et al., 2003; Dhingra and Gupta, 2020; Junadi and Sfenrianto, 2015).

Customers think that mobile banking apps are easier to use because they have simple user interfaces and a few steps to complete a transaction. Learnability is a basic principle of usability that says people are more likely to use technology that is simple to understand and use, even if they don't know much about it. Therefore, the following hypothesis is made:

Hypothesis 2: The effort expectancy has a positive effect on:

a) Perceived ease of use
b) Perceived usefulness

Social Influence

According to the definition, social influence is when other people change how someone thinks, feels, or acts. Various social actors engaged in decision-making, such as family, colleagues, peer groups, and others, can exert this influence (Dhingra and Gupta, 2020; Junadi and Sfenrianto, 2015). Prior research has shown that the attitudes of social groups or close individuals can significantly influence the adoption of electronic payment systems (Dhingra and Gupta, 2020; Farah et al., 2018). Additionally, certain empirical studies have demonstrated a robust correlation between social impact and the intention to utilize technology. For example, (Chiyangwa and Alexander, 2016) discovered that social influence significantly affected the intention to utilize multimedia communication services in their study of data from South Africa. In the same way, Lin et al. (2019) looked at data from 908 people in China and Korea and found that social influence had a positive effect on both nationalities' plans to use mobile payments. Consequently, the subsequent theory was proposed:

Hypothesis 3: The social influence has a positive effect on:

a) Perceived ease of use
b) Perceived usefulness

Facilitating Condition

Facilitating conditions encompass the benefits of utilizing electronic payment technologies, including internet-enabled devices and tools for accessing application software and networks. Concerning attitudes and behavioral intentions regarding the adoption of electronic payment technology, these factors are expected to exert a more significant positive influence (Lian and Li, 2021; Venkatesh et al., 2003). Numerous empirical studies have indicated that favorable conditions exert both direct and indirect effects on the behavioral intention to utilize mobile banking, with perceived usefulness serving as a mediating variable. One of these enabling conditions is having the right technology for mobile banking transactions, like a secure online platform, reliable internet access, and a functioning phone. Furthermore, it is deemed imperative for users to possess a requisite degree of digital and financial literacy to effectively navigate and utilize mobile banking services (Dhingra and Gupta, 2020; Madan and Yadav, 2016; Thakur and Srivastava, 2013). Therefore, the following is hypothesized.

Hypothesis 4: The facilitating condition has a positive effect on:

a) Perceived ease of use
b) Perceived usefulness
c) Intention to use face detection for mobile payment

Perceived Ease of Use and Perceived Usefulness

Perceived ease of use is how easy a person thinks mobile banking is to understand and use. Conversely, perceived utility denotes an individual's subjective evaluation that the implementation of a particular technology will enhance their job performance (Ho et al., 2020). Previous research reveals a positive correlation between users' attitudes towards mobile banking and their perceptions of its utility. Clients who think that mobile banking has real benefits and features are much more likely to use it. Perceived danger, compatibility, and resistance are significant factors that shape these perspectives, as identified by Raza et al. (2017). The perceived ease of use significantly influenced both attitude and perceived usefulness. The identification of perceived utility, perceived ease of use, and social impact as direct and indirect determinants of mobile banking usage corroborated the findings of Prastiawan et al. (2021). The substantial influence of perceived compatibility, social influence, and perceived ease of use on the perceived utility of mobile payment services was also emphasized (Dobrinić et al., 2021). Furthermore, Tertia and Nurbasari (2022) underscored the significance of perceived security, utility, and ease of use in fostering confidence in mobile banking. These studies collectively underscore the significant influence of perceived utility and ease of use on user attitudes and intentions regarding mobile banking.

Face detection technology is one way that mobile financial apps keep your information safe. It is similar to well-known methods such as fingerprint or iris identification (Beg et al., 2024; Nosrati et al., 2024). The main goal of facial recognition is to take a picture of someone's face with the camera on a mobile device. We extract the eyes, lips, and ears from the picture and scrutinize them more closely. This method transforms the face image into a comparable data pattern. Next, we cross-reference the returned data with an existing database containing user profiles that have been granted permission. Applying deep learning algorithms significantly improves the accuracy of facial recognition. A wide range of industries, including retail, government services, and healthcare, have also adopted face recognition technology (Zhang, 2022). Consequently, researchers propose the following theories:

Hypothesis 5: The perceived ease of use has a positive effect on the attitude toward using face detection for mobile payment.

Hypothesis 6: The perceived usefulness has a positive effect on the attitude toward using face detection for mobile payment.

Attitude Toward Using Face Detection Technology

According to psychology, attitude is a person's long-term evaluation of a particular behavior that captures the emotions associated with engaging in it, whether they are positive or negative. This evaluation can be gauged by how much a person expresses that they feel either positively or negatively about the activity. Attitudes are known to significantly predict behavioral intentions, such as the adoption of new technologies like face identification in mobile banking (Ho et al., 2020).

Regarding security and user experience, the findings of research on face detection technologies in mobile banking are promising. In response to security concerns regarding facial recognition, Patel et al. (2016) created a technique for detecting face spoofing on smartphones. This subject is particularly pertinent to mobile banking, where security is crucial. In their comprehensive analysis of face recognition algorithms, (Kumar et al. 2019) emphasized the possibility of enhancing the user experience in mobile banking apps. Wijaya et al. (2019) further demonstrated the usefulness of face authentication in mobile phones by achieving high authentication rates and satisfactory performance. These results demonstrate that integrating facial recognition technology into mobile banking can improve user experience and security. Furthermore, Zhang, et al. (2018) pointed out several factors that are particularly pertinent to face detection technology, including perceived utility, perceived ease of use, and trust in the adoption of mobile banking technology. Therefore, we propose the following hypothesis:

Hypothesis 7: The attitude toward using has a positive effect on the intention to use face detection for mobile payment.

Age, Gender, and Mobile Experience as a Moderator

Studies on technology acceptance have increasingly focused on the influence of demographic and experiential variables as moderators, especially in the context of mobile and biometric technology adoption. However, previous research has yielded inconclusive results. In mobile health applications, age and smartphone experience significantly influenced the relationship between performance expectancy and usage intention. Additionally, other factors varied by age and gender; older men exhibited greater intention when effort was minimal, whereas younger men displayed increased intention under more favorable conditions (Nunes et al., 2019).

Research on mobile wallet adoption indicated that both gender and age significantly influenced the relationships between antecedents and user attitudes or intentions, with more pronounced effects observed among male and younger users (Chawla and Joshi, 2020).

In addition to direct relationships, researchers have emphasized the potential moderating influence of demographic and experiential variables. The UTAUT model posited that age and gender influence the impact of expectancy and social constructs on behavioral intention (Venkatesh et al., 2003). Younger users are typically more influenced by perceived usefulness and ease of use, whereas older individuals may experience heightened technology anxiety and depend more on facilitating conditions (Morris and Venkatesh, 2000). Gender disparities have been identified, with men exhibiting a greater focus on performance and women being more swayed by social norms (Riquelme and Rios, 2010). Furthermore, mobile experience or digital literacy has become a significant moderator in technology adoption research. Previous research indicates that seasoned users often disregard ease of use as a factor, whereas novice users prioritize usability and support (Moustakim and Mohammed, 2025). These results indicate that demographic factors and previous experience may influence individuals' perceptions and adoption of face detection technology in mobile banking.

The amalgamation of expectancy, usability, and attitudinal constructs, alongside demographic and experiential moderators, establishes a thorough framework for comprehending the behavioral intention to embrace face detection technology in mobile banking. This study builds on previous research by empirically examining the moderating effects of age, gender, and mobile experience, thereby making it easier to comprehend biometric technology acceptance in the context of financial services. After looking at the literature, we came up with the following hypotheses:

Hypothesis 8a: Age will moderate the relationship between performance expectancy and intention to use face detection.

Hypothesis 8b: Age will moderate the relationship between attitude toward using and intention to use face detection.

Hypothesis 8c: Age will moderate the relationship between facilitating condition and intention to use face detection.

Hypothesis 9a: Gender will moderate the relationship between performance expectancy and intention to use face detection.

Hypothesis 9b: Gender will moderate the relationship between attitude toward using and intention to use face detection.

Hypothesis 9c: Gender will moderate the relationship between facilitating condition and intention to use face detection.

Hypothesis 10a: Mobile experience will moderate the relationship between performance expectancy and intention to use face detection.

Hypothesis 10b: Mobile experience will moderate the relationship between attitude toward using and intention to use face detection.

Hypothesis 10c: Mobile experience will moderate the relationship between facilitating condition and intention to use face detection.

The conceptual framework of this study delineates the relationships among the key variables, as informed by the proposed hypotheses. The model embodies the theoretical underpinnings and directs the empirical inquiry, as illustrated in Fig. 1.

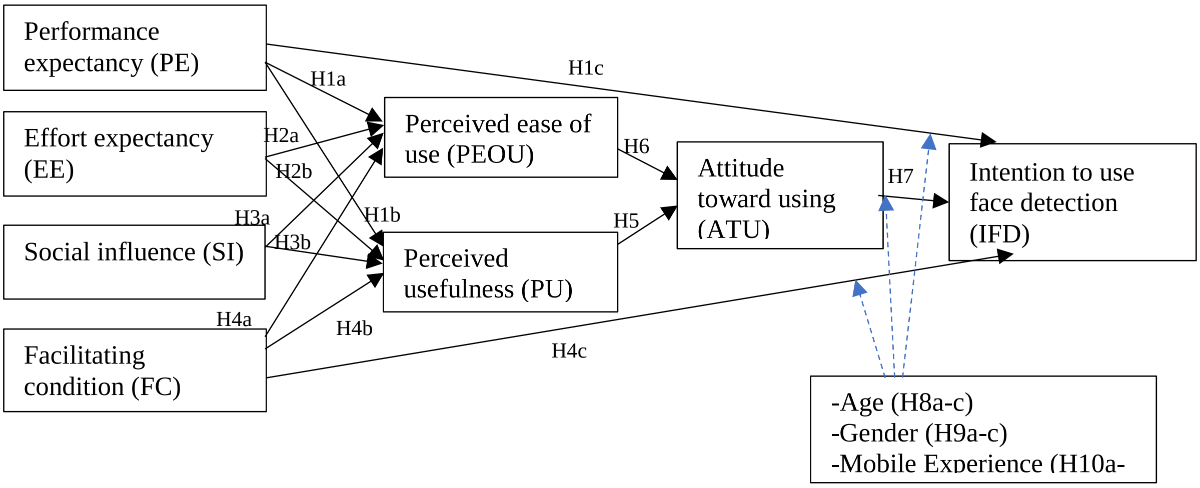

Fig. 1: Conceptual model of the research

Materials and Methods

Sample

This study targeted users of mobile banking applications in Thailand. Given the exploratory nature of this behavioral study and its reliance on Partial Least Squares Structural Equation Modeling (PLS-SEM), the required sample size was determined based on recent methodological guidelines for SEM research. According to Hair et al. (2014), a minimum sample size should consider the maximum number of structural paths pointing to a construct and ensure sufficient statistical power (typically 0.80) at a 5% significance level.

Using G*Power software and assuming a small to medium effect size ($f^2 = 0.10$) with a power of 0.80, the minimum recommended sample size was approximately 150–200 respondents, depending on model complexity. However, to enhance robustness, minimize sampling error, and accommodate possible data exclusions, this study collected a total of 539 valid responses. This sample size far exceeds conventional thresholds and aligns with contemporary SEM best practices, which recommend oversampling for improved model estimation accuracy and generalizability (Kock and Hadaya, 2018; Kyriazos, 2018).

Survey Instrument and Data Collection

Prior to data collection, ethical clearance was requested through an exemption process for research involving human subjects. Upon approval, questionnaires were distributed to mobile banking users through both online and offline channels to ensure convenience and accessibility.

An online version of the questionnaire was created using Google Forms and shared via social media to reach a broader audience. Participants who completed the survey were provided an opportunity to enter a prize draw as an incentive for participation.

The questionnaire consisted of 25 items measuring eight constructs, alongside eight demographic and general perception questions. All measurement items were adapted from prior studies to fit the context of mobile banking, and responses were rated using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Reliability and Validity Assessment

To evaluate the measurement model, several statistical tests were conducted. Convergent validity was assessed through standardized factor loadings and Average Variance Extracted (AVE). Loadings greater than 0.70 and AVE values above 0.50 indicate satisfactory convergence (Hair et al., 2014). Internal consistency reliability was confirmed using Composite Reliability (CR) and Cronbach's alpha, with acceptable thresholds above 0.70 for both metrics (Henseler et al., 2015).

Data Analysis

Statistical analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0 (Ringle et al., 2013). The choice of sample size meets Kyriazos (2018) recommendation for using SEM with questionnaires containing 40 or more items. According to Jhantasana (2023), a minimum sample size of 385 ensures robustness for SEM-based analysis.

To investigate the moderating effects, three demographic variables were considered: Gender, age, and mobile banking experience. For gender, the analysis was conducted directly based on the original responses provided by participants, without regrouping. For age, participants were classified into two groups: 189 respondents aged 20 years or below and 350 respondents aged 20 years or above. For mobile banking experience, respondents were categorized into two groups: Those with five years of experience or less (n = 399, 74.1%) including 78 with less than three years and 321 with three to five years and those with more than five years of experience (n = 140, 25.9%) including 121 with six to ten years and 19 with more than ten years.

The demographic distribution of respondents is presented in Table 4. These categorizations were subsequently employed in the moderation analysis within the structural model.

Measurement Model Assessment

We evaluated the notions' convergent validity and reliability using predetermined criteria. The dependability of the items was evaluated using factor loadings. Hair et al. (2021) determined that a criterion of 0.7 or higher was considered sufficient. Table 1 displays the factor loadings for each item. We removed FC4, which had a loading value of less than 0.7, to ensure build integrity.

Construct reliability was assessed using Cronbach's alpha and composite reliability. As advised by Henseler et al. (2015), a value of 0.7 or greater for each index denotes acceptable reliability. All builds exceeded this criterion, as confirmed by Table 1, with the exception of the one that had the removed piece (FC4). Convergent validity represents how much a construct captures the expected variance. We used the Average Variance Extracted (AVE) approach to assess convergent validity. A construct is considered to explain more than half of the variance in its items if the AVE is 0.5 or greater, as per the findings of Hair et al. (2014). As shown in Table 2, all constructs achieved AVE values larger than 0.5, indicating convergent validity.

Moreover, the full details of the measurement items and their corresponding questionnaire statements are provided in Appendix A.

Furthermore, item-total correlations were computed to evaluate each item's discriminatory potential. The ability of an item to distinguish between people who have high and low levels of the measured construct is known as discriminatory power. According to Black et al. (2010), an item-total correlation of more than 0.3 indicates that all items significantly contribute to the discrimination of individuals on the construct. In conclusion, the analysis proved the constructs' convergent validity and reliability, with the exception of the construct (FC4) that included the deleted item.

To assess discriminant validity, the Fornell-Larcker criterion was utilized (Fornell and Larcker, 1981; Hair et al., 2014).

The square root of the average variance extracted, or AVE, for each construct (diagonal elements in the correlation matrix) must be greater than the correlations between any two constructs in order for this requirement to be satisfied.

Table 1: Reliability and validity assessment of measurement constructs

Constructs	Items	Factor loadings	Item-total correlation	Cronbach's Alpha	CR	AVE
Performance expectancy; PE	PE1	0.788	0.524	0.791	0.878	0.707
	PE2	0.877	0.705			
	PE3	0.855	0.662			
Effort Expectancy; EE	EE1	0.851	0.621	0.795	0.879	0.708
	EE2	0.815	0.640			
	EE3	0.858	0.655			
Social Influence; SI	SI1	0.817	0.628	0.856	0.913	0.778
	SI2	0.917	0.807			
	SI3	0.908	0.771			
Facilitating condition; FC	FC1	0.823	0.607	0.809	0.887	0.724
	FC2	0.876	0.708			
	FC3	0.853	0.660			
	FC4*	*0.472	0.288*			
Perceived ease of use; PEOU	PEOU1	0.766	0.498	0.776	0.871	0.693
	PEOU2	0.886	0.728			
	PEOU3	0.841	0.641			
Perceived usefulness; PU	PU1	0.787	0.559	0.780	0.872	0.695
	PU2	0.872	0.685			
	PU3	0.839	0.615			
Attitude toward using ATU	ATU1	0.930	0.831	0.899	0.937	0.832
	ATU2	0.913	0.795			
	ATU3	0.893	0.773			
Intention to use face detection; IFD	IFD1	0.932	0.846	0.920	0.949	0.862
	IFD2	0.930	0.837			
	IFD3	0.924	0.829			

Note: CR = Composite reliability, AVE = Average Variance Extracted

***** The item will be removed when the SEM statistic is run

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Table 2: Discriminant validity and correlation matrix

	PE	EE	SI	FC	PEOU	PU	ATU	IFD
Mean	4.478	4.351	3.528	4.353	4.238	4.386	4.153	4.225
S.D.	0.626	0.628	1.067	0.677	0.722	0.690	0.838	0.845
PE	0.841							
EE	0.692**	0.841						
SI	0.128**	0.254**	0.882					
FC	0.580**	0.575**	0.207**	0.851				
PEOU	0.562**	0.598**	0.304**	0.550**	0.832			
PU	0.631**	0.595**	0.266**	0.581**	.723**	0.834		
ATU	0.456**	0.498**	0.337**	0.426**	.671**	.747**	0.912	
IFD	0.482**	0.485**	0.318**	0.433**	.645**	.689**	.783**	0.928

Note: The square root of AVE is shown on the diagonal of the matrix in bold
** Correlation is significant at the 0.01 level (2-tailed)

Table 3: Model Fit Indices

Fit Index	Saturate model	Estimated model	Recommended Threshold	Interpretation
SRMR (Standardized Root Mean Square Residual)	0.065	0.080	≤ 0.08 (Hair et al., 2020; Dash and Paul, 2021)	Good fit
d_ULS (Squared Euclidean Distance)	1.588	2.396	Closer to 0 is better (Henseler et al., 2016; Dash and Paul, 2021)	Acceptable fit
d_G (Geodesic Distance)	0.583	0.742	Closer to 0 is better (Henseler et al., 2016; Dash and Paul, 2021)	Acceptable fit
Chi-square	1912.052	2444.118	Sensitive to sample size; not recommended as a sole criterion (Hair et al., 2014; Henseler et al., 2016)	
NFI (Normed Fit Index)	0.792	0.734	≥ 0.90 (Dash and Paul, 2021)	Acceptable fit

As shown in Table 2, discriminant validity for the constructs in the current study is shown by the fact that all diagonal elements (square root of AVE) are greater than the equivalent off-diagonal elements (correlations between constructs).

Model Fit Indices

To evaluate the overall model fit, we adopted the goodness-of-fit criteria recommended for partial least squares structural equation modeling (PLS-SEM). The results are summarized in Table 3. The Standardized Root Mean Square Residual (SRMR) for the estimated model was 0.080, which is marginally above the conservative threshold of 0.08. Nevertheless, it remains within a tolerable range for exploratory research (Hair et al., 2020; Dash and Paul, 2021).

Additional fit indices, including the squared Euclidean distance (d ULS = 2.296) and geodesic distance (d_G = 0.742), both remain within acceptable thresholds, as values closer to zero are preferred. These values support the overall adequacy of the model's fit to the observed data (Henseler et al., 2016; Dash and Paul, 2021).

The Normed Fit Index (NFI) for the estimated model was 0.792, which falls slightly below the recommended cut-off of 0.90, indicating a moderate but still acceptable level of model fit (Bentler and Bonett, 1980; Dash and Paul, 2021).

It is important to note that several global fit indices commonly used in covariance-based SEM (CB-SEM) such as the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Goodness-of-Fit Index (GFI) are not applicable to variance-based SEM techniques like PLS-SEM. This is due to the fundamental difference in estimation objectives: PLS-SEM focuses on maximizing explained variance in endogenous constructs, whereas CB-SEM emphasizes reproducing the observed covariance matrix (Hair et al., 2020).

Accordingly, SmartPLS provides appropriate alternative fit measures tailored for prediction-oriented models. The inclusion of SRMR as a residual-based index and NFI as a comparative index aligns with established best practices in PLS-SEM. Their use ensures that the proposed research model meets methodological standards for assessing model adequacy within the variance-based SEM framework (Dash and Paul, 2021).

Results

Descriptive Statistic

As part of the data-gathering process, respondents in

Thailand were provided access to an online questionnaire. 539 individuals, all currently enrolled in mobile banking services, completed the study. By restricting participation to members of this demographic, the study aimed to increase the quality of the data gathered and give a sample with direct experience with mobile banking. Table 4 provides a summary of the study participants' demographic data. There was a gender bias in the sample, with 22.10 of participants being men and 75.50% of participants being women. The age distribution showed a concentration in the young adult range, with 63.30% of respondents falling into the 20–30 age group. 91.10% of mobile banking users reported having a monthly income of less than 15,000 baht, indicating that their income levels were largely modest.

With 73.50% of participants saying they used mobile banking more than ten times a week, the frequency of use was high. 13.10% more people said they used it six to ten times a week, 11.50% said they used it three to five times a week, and 1.90% said they used it fewer than three times a week. The study also looked at how the mobile banking app incorporates facial recognition. According to the findings, 69.90% of users of mobile banking said they used face detection for other purposes, such as secure authentication. On the other hand, 30.10% of users had not yet used this feature.

Table 4: Demographic Characteristics (N = 539)

Item	Group Name	Frequency	Ratio (%)
Gender	Male	119	22.10
	Female	407	75.50
	Not specify	13	2.40
Age	< 20	189	35.10
	20 – 30	341	63.30
	> 30	9	1.70
Income	< 15,000 baht	491	91.10
	15,001 – 30,000 baht	36	6.70
	30,001 – 50,000 baht	6	1.10
	> 50,000 baht	6	1.10
Frequency of use of mobile banking	< 3 times per week	10	1.90
	3 – 5 times per week	62	11.50
	6 – 10 times per week	71	13.20
	> 10 times per week	396	73.50
Experience in using mobile banking	< 3 years	78	14.50
	3-5 years	321	59.60
	6-10 years	121	22.40
	> 10 years	19	3.50
Experience in using face detection	Yes	162	30.10
	No	377	69.90

Structural Model Assessment

The suggested model's explanatory power is assessed through a comparison of the observed and anticipated values of the dependent variables. Path coefficients and R-squared (R^2) are important metrics for evaluating structural models, according to Hair et al. (2014). As illustrated in Figure 2, the model's R^2 values are 47.70 for PEOU, 51.00for PE, 59.00 for ATU, and 64.30% for IFD. In the context of route analysis, Figure 2 and Table 5 present the path coefficients and p-values for each hypothesis.

The analysis of hypotheses H1a–H1c examined the role of performance expectancy (PE) in shaping user perceptions and behavioral intention to adopt face detection in mobile banking. The results show that PE has a significant positive effect on perceived ease of use (H_{1a}: $\beta = 0.216$, $p<0.01$) and perceived usefulness (H_{1b}: $\beta = 0.333$, $p<0.01$), suggesting that users who believe face detection offers efficiency and utility also perceive it as easier to use and more beneficial. These findings are consistent with prior studies highlighting the central role of PE in influencing user perceptions of technology adoption (Venkatesh et al., 2003; Abrahão et al., 2016).

However, the direct path from PE to intention to use face detection (H_{1c}: $\beta = 0.046$, $p>0.10$) was not statistically significant. This result contrasts with the Unified Theory of Acceptance and Use of Technology (UTAUT), which posits a strong positive relationship between PE and behavioral intention. Nonetheless, this outcome is not unique. Yuliantie (2024) similarly discovered that satisfaction mediated the relationship, with PE not having a significant direct effect on behavioral intention.

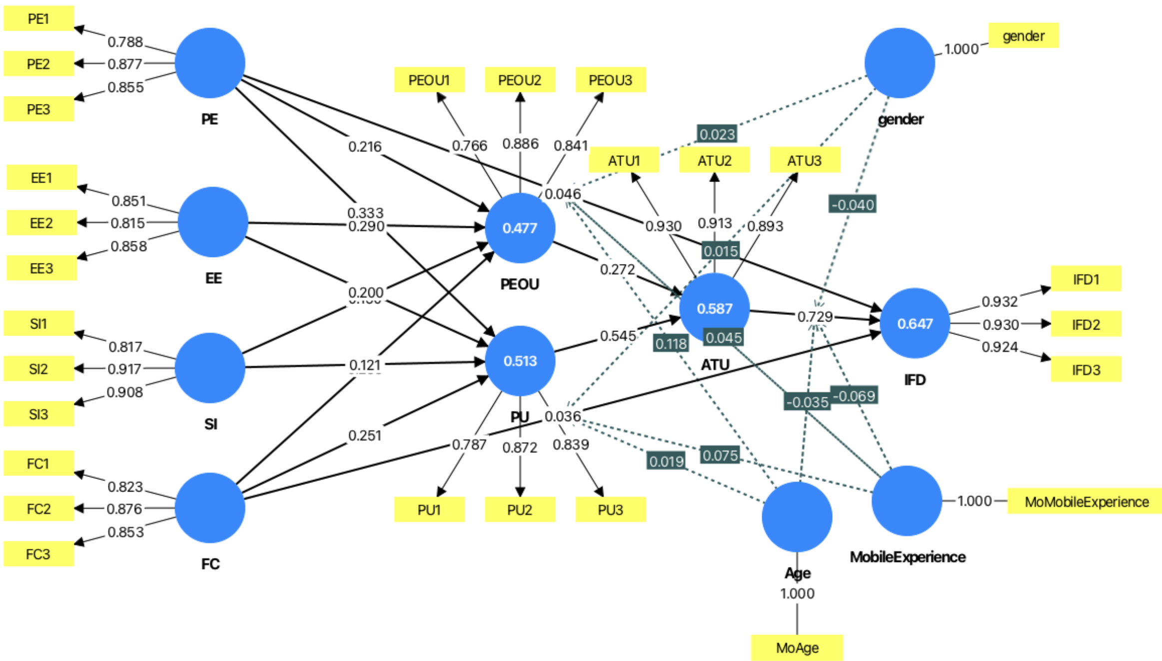

Fig. 2: PLS-SEM algorithm results

Table 5: Structural model results

Hypothesis	Path Coefficient	t-value	p-value	Result
H1a: PE -> PEOU	0.216	4.214	0.000***	Supported
H1b: PE ->PU	0.333	6.758	0.000***	Supported
H1c: PE -> IFD	0.046	0.735	0.231	Not Supported
H2a: EE -> PEOU	0.290	5.298	0.000***	Supported
H2b: EE -> PU	0.200	3.814	0.000***	Supported
H3a: SI -> PEOU	0.150	3.860	0.000***	Supported
H3b: SI -> PU	0.121	3.324	0.000***	Supported
H4a: FC -> PEOU	0.233	4.618	0.000***	Supported
H4b: FC ->PU	0.251	5.129	0.000***	Supported
H4c: FC -> IFD	0.036	0.503	0.307	Not Supported
H5: PU -> ATU	0.545	10.189	0.000***	Supported
H6: PEOU -> ATU	0.272	4.686	0.000***	Supported
H7: ATU -> IFD	0.729	8.594	0.000***	Supported
H8a: Age x PE -> IFD	0.118	1.410	0.079*	Supported
H8b: Age x ATU -> IFD	-0.035	0.316	0.376	Not Supported
H8c: Age x FC -> IFD	0.019	0.196	0.422	Not Supported
H9a: Gender x PE -> IFD	0.023	0.659	0.255	Not Supported
H9b: Gender x ATU -> IFD	-0.040	1.050	0.147	Not Supported
H9c: Gender x FC -> IFD	0.015	0.411	0.340	Not Supported
H10a: MobileEx x PE -> IFD	0.045	0.506	0.307	Not Supported
H10b: MobileEx x ATU -> IFD	-0.069	0.584	0.279	Not Supported
H10c: MobileEx x FC -> IFD	0.075	0.749	0.227	Not Supported

Note: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01

This suggests that PE may shape intention indirectly through mediating variables such as satisfaction, trust, or attitude, rather than exerting a direct influence.

In the Thai context, this finding may be explained by the high familiarity of users with mobile banking applications. Since performance-related expectations such as speed, efficiency, and convenience are already well-established and widely experienced, PE may not serve as a decisive factor in encouraging adoption of additional features like face detection. Instead, factors such as trust in biometric security, ease of use, and social influence may play a more prominent role in determining behavioral intention. Thus, while PE remains important in shaping perceptions of usefulness and ease of use, its direct impact on intention appears to be diminished in contexts where baseline performance expectations are already met.

The next assumption, H_{2a} ($\beta = 0.290$, $p<0.01$), describes the relationship between effort expectancy and perceived ease of use. This implies that effort expectancy has a major impact on how simple people consider mobile banking payments to be. H_{2b} ($\beta = 0.200$, $p<0.01$) showed that effort expectancy had a favorable impact on the perceived usefulness of mobile banking payments. Previous studies have repeatedly shown that effort expectancy has a considerable impact on how easy a range of applications and services are judged to be to use. Given its capacity to influence consumers' intentions and actual use of a product or service, this relationship is particularly important when it comes to the adoption and use of technology (Venkatesh et al., 2003; Dhingra and Gupta, 2020; Junadi and Sfenrianto, 2015). As a result, the theories H2a and H2b are supported.

However, perceived utility and familiarity are two more elements that may have an impact on the relationship between effort expectancy and perceived ease of use (Gideon, 2021; Perera, 2021). The perceived convenience of using mobile banking payments is positively influenced by social influence (H_{3a}, $\beta = 0.150$, $p<0.01$). H_{3b} ($\beta = 0.121$, $p<0.01$) illustrates the relationship between perceived utility and social influence. It implies that particular people, like friends, family, or acquaintances, positively influence how useful people consider mobile banking technology. Similarly, previous studies have shown that social influence has a major impact on how easy and valuable people perceive a range of technologies, including online social networks (Qin et al., 2011), online communities (Ryu and Choi, 2008), and course delivery systems. The association between enabling conditions and perceived convenience of use is shown in H_{4a} ($\beta = 0.233$, $p<0.01$).

We have established that by making full use of all mobile device resources including the availability of mobile phones, technological expertise, and prior familiarity with other technologies the perceived ease of use in mobile banking may be enhanced. The connection between perceived usefulness and facilitating conditions is shown in H_{4b} ($\beta = 0.251$, $p<0.01$), suggesting that the environment of enabling conditions has a beneficial impact on the perceived utility of mobile banking payments. The support for H_{3a}, H_{3b}, H_{4a}, and H_{4b} provides evidence in favor of the previously stated idea.

The connection between the facilitating condition and intention to utilize face detection is validated by H_{4c} ($\beta = 0.036$, $p = 0.307$, $p>0.10$); however, it suggests that the facilitating condition is not significantly involved in the face recognition function of mobile banking. H_{4c} is therefore rejected. Furthermore, Horstmann, and Ansorge (2006); Doi and Shinohara (2013) found that a number of characteristics, such as the direction of gaze and the valence of the emotion, affect how well facial expressions are detected. On the other hand, it is possible that there is little or no correlation between these favorable circumstances and the decision to use face detection, according to Takahashi and Watanabe (2015); Heeks and Azzopardi (2015). According to research by Takahashi and Watanabe (2015), object perception as a feature can enhance object detection; however, this may not always align with the objective of using face detection. In a similar line, Heeks and Azzopardi (2015) found that a complex stimulus's configuration does not increase the detectability of the stimulus independent of awareness. This discovery may also influence the decision to employ face detection. Consequently, these favorable circumstances might influence the effectiveness of facial expression recognition, but they might not have a significant effect on the intention to utilize face detection.

Moreover, the results of this study demonstrate that attitudes toward using face detection are positively impacted by perceived utility and ease of use ($\beta = 0.545$, $p<0.01$) and $\beta = 0.272$, $p<0.01$, respectively. Similarly, research shows time and time again that users' attitudes toward using a technology or system are positively impacted by perceived usefulness as well as the ease of use. Consequently, this upbeat attitude leads to a rise in the system's actual usage (Raza et al., 2017; Anaam et al., 2021; Raksadigiri and Wahyuni, 2020; Wiprayoga and Widagda, 2023). As such, it can be assumed that H5 and H6 are given support.

Moreover, there is a significant positive correlation between attitude toward employing face detection and intention to utilize it ($\beta = 0.729$, $p<0.01$). Several factors may influence the relationship between users' intention to adopt face detection technology and their attitudes toward its use. This understanding is furthered by Luhandjula et al. (2014); Zhang, (2022), who examine the ways in which particular attributes and features of face identification systems impact user acceptance. Luhandjula et al. (2014) primarily focus on the use of face detection for intent recognition, with a special emphasis on the elderly and users with severe disabilities. Zhang (2022), on the other hand, focuses specifically on Chinese users while examining the impact of user resistance to innovation and features in facial recognition payment systems on the intention to use. Both studies show that system attributes and user resistance have a major impact on the intention to utilize face detection technologies. Consequently, Hypothesis 7 (H_7) is supported by this evidence. The results of the moderation analysis reveal that among the three moderators tested—age, gender, and mobile experience only age exerted a significant moderating effect (H_{8a}: Age × PE → IFD). As illustrated in Figure 3, the positive slope for older users indicates that performance expectancy has a stronger effect on the intention to adopt face detection in mobile banking for this group, while the effect is weaker among younger users. This supports the argument of Morris and Venkatesh (2000), who emphasized that older individuals often require stronger evidence of performance benefits before committing to new technologies. In the Thai context, this finding highlights that older users, who may be more cautious and selective in adopting digital innovations, are more likely to be convinced by the tangible advantages of efficiency and security that face detection provides.

However, age did not have significant moderating effects on the relationship between attitude toward use (ATU) and IFD (H_{8b}), nor on the relationship between Facilitating Conditions (FC) and IFD (H_{8c}). As shown in Figures 4 and 5, the slopes of both age groups are almost parallel, suggesting that age does not meaningfully alter the strength of these relationships. In other words, regardless of whether users are younger or older, their attitudes and perceptions of facilitating conditions influence their intention to adopt face detection in a similar way.

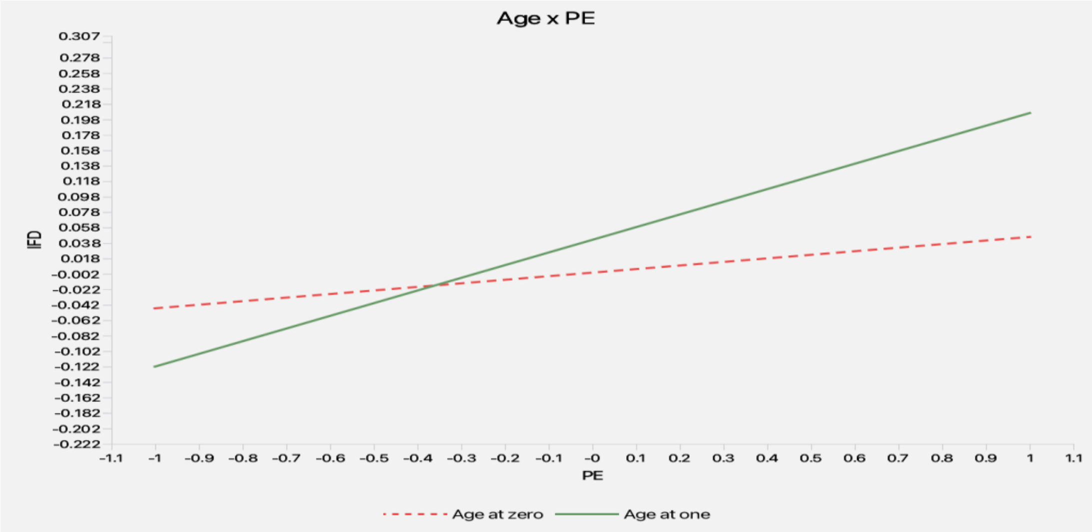

Fig. 3: Moderating effect of age on the relationship between performance expectancy and intention to use face detection

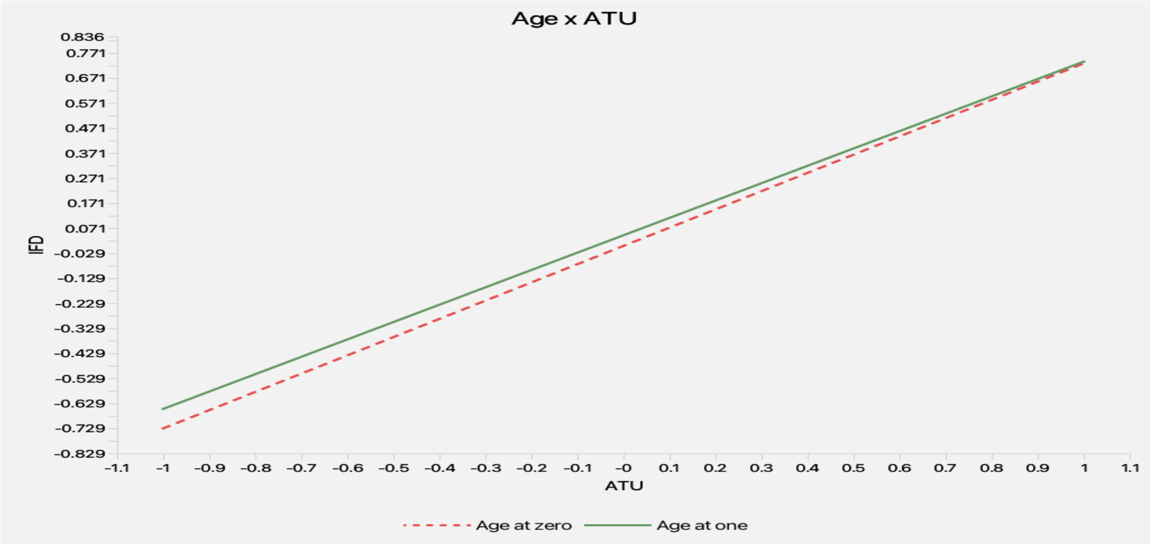

Fig. 4: Interaction effect of age on the relationship between attitude toward use and intention to use face detection

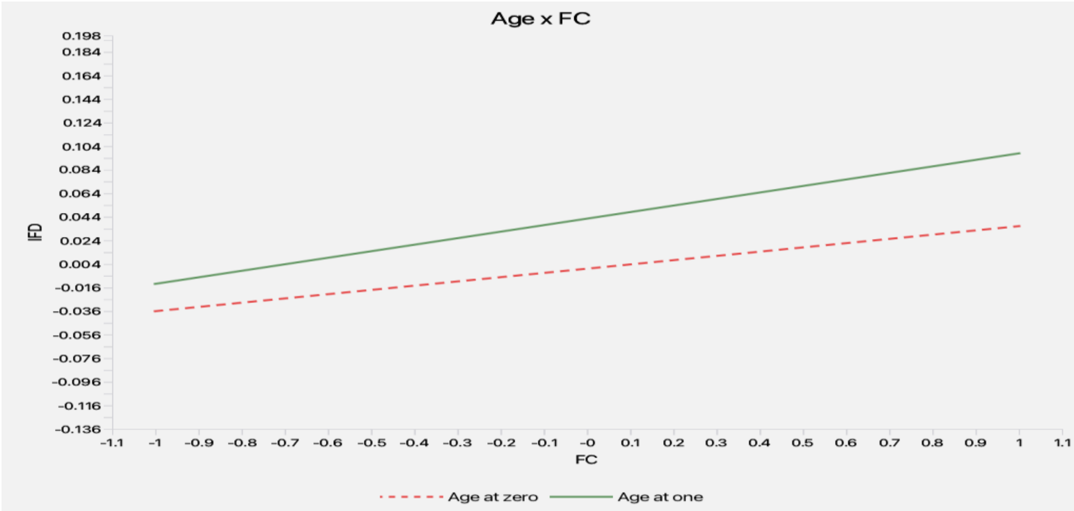

Fig. 5: Interaction effect of age on the relationship between facilitating conditions and intention to use face detection

One possible explanation in the Thai context is that both younger and older users may already have strong familiarity with mobile banking systems, which normalizes attitudes and infrastructure support across age groups. Younger users are highly accustomed to mobile applications, while older users may increasingly rely on support from banks and fintech providers that simplify adoption. As such, the role of age in moderating ATU and FC becomes less pronounced, leading to non-significant results in H8b and H8c.

Moreover, gender (H9a H9c) and mobile experience (H10a H10c) did not significantly moderate any of the hypothesized relationships. This suggests that in Thailand, male and female users perceive face detection in mobile banking in largely similar ways. Unlike in some international studies, where men were found to be more performance-driven and women more socially influenced (Riquelme and Rios, 2010), the widespread adoption of mobile banking in Thailand across both genders appears to have reduced such differences. Both male and female respondents are already accustomed to digital financial services, which may explain the absence of a moderating effect of gender in this study.

Similarly, the absence of a moderating effect for mobile experience indicates that users with both short-term and long-term exposure to mobile banking demonstrate comparable adoption behaviors. In the Thai context, where digital banking penetration is already high and mobile payment systems are normalized, the length of experience does not substantially alter the way users evaluate new features such as biometric authentication. This finding aligns with recent research suggesting that once users achieve a certain threshold of digital literacy, experience becomes less decisive in influencing behavioral intention, with trust, security, and social influence emerging as more relevant determinants (Moustakim and Mohammed, 2025).

Taken together, these results highlight that while age remains an important moderator, gender and mobile experience appear to have less relevance in explaining variations in the intention to adopt face detection in mobile banking within the Thai context. This suggests that demographic differences are becoming less influential in digital finance adoption as technology becomes mainstream, and future studies should consider psychological or contextual moderators (e.g., trust, satisfaction, or risk perception) to capture the nuances of user adoption behavior.

Discussion and Contributions

This study reinforces the applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) in investigating the behavioral intention to adopt facial recognition in mobile banking. By offering empirical evidence from Thailand a region underrepresented in existing biometric authentication literature this work enriches the growing discourse on digital trust and user behavior in financial technologies.

The study found support for most UTAUT-based relationships, but two notable exceptions emerged. The direct effect of performance expectancy on intention was not significant, consistent with findings from Yuliantie (2024), suggesting that performance benefits may influence intention indirectly through mediators such as satisfaction, trust, or attitudes rather than through a direct path. Similarly, facilitating conditions did not directly affect intention, highlighting that infrastructural or technical support may be less decisive in contexts like Thailand, where baseline access to mobile banking is already widespread and normalized.

In terms of moderators, only one pathway age moderating the effect of performance expectancy on intention—was supported. The results indicate that performance-related benefits strongly influence older users more than younger ones. However, other moderating effects, including age on attitude and facilitating conditions, gender, and mobile experience, were not significant. This implies that Thai users, regardless of gender or length of mobile banking experience, perceive biometric authentication in a relatively similar way. Such findings differ from international evidence (Riquelme and Rios, 2010; Chawla and Joshi, 2020), where gender and experience often matter, and suggest that Thailand's high penetration of digital banking may have reduced demographic disparities in adoption behavior.

A key contribution of this research is its contextualization of UTAUT within Thailand's biometric mobile banking environment. The study highlights that while user perceptions of usefulness, ease of use, and attitudes remain strong predictors of adoption, demographic factors such as gender and experience play a diminished role. Instead, issues of trust, privacy, and security appear central to user confidence.

Building on these empirical results, the following practical and policy implications can be drawn for the Thai banking sector. From a policy and managerial perspective, these findings carry important implications. For banks, the priority should not lie solely in enhancing technical infrastructure but rather in strengthening user-centric features that directly shape perceptions of usefulness, simplicity, and attitudes. Banks should also implement transparent data protection protocols and clear communication strategies regarding the collection and use of biometric data to build user trust. In particular, compliance with Thailand's Personal Data Protection Act (PDPA) requires banks to obtain explicit consent from users before collecting or processing biometric data and to ensure that such data is used strictly for necessary and lawful purposes. This implies that banks must design authentication processes that not only meet security requirements but also respect user privacy, minimizing data retention and applying safeguards against unauthorized access.

For policymakers, especially the Bank of Thailand, these insights emphasize the importance of designing regulatory frameworks that balance innovation with privacy protection. By aligning biometric authentication systems with PDPA principles of necessity, proportionality, and informed consent, policymakers can help foster user confidence while ensuring compliance with national legal standards. Additionally, communication campaigns should highlight performance-related benefits, particularly for older users, while addressing broader trust and security concerns for the general population.

Practical recommendations for Thai banks emerge from these findings. First, banks must obtain explicit user consent in compliance with PDPA and ensure that biometric data is processed only for necessary and lawful purposes. Second, transparency in biometric data handling should be strengthened through clear communication and accessible privacy notices. Third, privacy-by-design measures must be integrated into system architecture, including encryption, anonymization, and limited data retention. Fourth, communication strategies should be tailored by age group—emphasizing performance and security for older users while highlighting convenience and usability for younger ones. Fifth, banks should develop internal governance frameworks to ensure compliance with PDPA principles of necessity and data minimization. Sixth, collaboration with regulators and fintech ecosystems will ensure alignment with national strategies and regulatory standards. Finally, banks should foster public trust through education campaigns that clarify both the benefits and protections associated with biometric authentication.

Collectively, this study contributes by contextualizing the UTAUT model within the framework of Thai biometric banking, offering insights that extend beyond generic mobile technology adoption literature. It further highlights region-specific implications for the design, governance, and regulation of mobile financial services that align with local user behaviors, regulatory landscapes, and cultural expectations.

Conclusion

The purpose of this study was to identify the factors influencing Thai consumers' intention to use facial recognition technology for mobile payments. By extending the UTAUT framework with moderators (age, gender, and mobile experience), the research offers empirical evidence about how both technological and demographic factors shape adoption in a localized setting.

The findings indicate that most hypothesized relationships were significant: Performance expectancy, effort expectancy, social influence, perceived ease of use, perceived usefulness, and attitude toward use all played crucial roles in shaping adoption intention. However, the direct influence of performance expectancy and facilitating conditions on intention was not supported, underscoring the possibility that these factors exert their effects indirectly through mediators. Among the moderators, only age partially influenced adoption, while the effects of gender and mobile experience were not significant, suggesting that demographic distinctions in Thailand have become less important in explaining mobile banking behavior.

These findings carry several implications. For theory, they extend UTAUT and offer lessons for the broader UTAUT2 framework by demonstrating that not all core constructs or moderators hold equally across cultural and technological contexts. While UTAUT2 emphasizes additional user-centric elements such as hedonic motivation, price value, and habit, this research demonstrates the contextual importance of trust, privacy, and perceived security as comparable behavioral drivers within biometric mobile banking. The findings underscore the necessity for localized adaptations of UTAUT2 that incorporate privacy and trust dimensions to accurately reflect user perceptions of biometric technologies in nascent digital economies.

The results show that Thai banks should focus on building user trust, making sure that biometric data is safe, and making sure that users understand how their data is being used. Furthermore, system designs that highlight performance benefits may be particularly effective in engaging older users, while ease of use and trust should be emphasized for the wider population.

For users of mobile phones, mobile payments are a cutting-edge financial technology with several advantages. These benefits include novel and captivating consumer experiences, improved transactional ease, and heightened productivity via time-saving measures. Mobile payments also benefit parties other than the customer. Every stakeholder in the ecosystem of mobile payments is eligible to receive rewards. The list includes government organizations, service providers, hardware and software suppliers, and financial institutions like banks and card processors.

Still, this study identifies certain limitations. It primarily follows the UTAUT model, omitting potential domain-specific extensions. Future research may extend the model by incorporating biometric-related constructs such as trust in facial recognition, perceived risk, trust in technology, and data sensitivity, which have become increasingly relevant under Thailand’s Personal Data Protection Act (PDPA). Integrating these variables could offer more details about how users’ perceptions of security, transparency, and data control influence their acceptance of biometric authentication in mobile banking. Furthermore, extending the theoretical framework to include UTAUT2 constructs such as habit, hedonic motivation, and price value may further enhance the explanatory power of behavioral intention models in this domain.

Additionally, other behavioral, technological, and socio-demographic factors may be explored in future studies, including trialability (Ho et al., 2020), self-efficacy (Dhingra and Gupta, 2020), and customer trust (Ho et al., 2020). Moreover, the current study did not capture respondents’ educational background or urban–rural distribution, which may also influence technology adoption behaviors. Future research should therefore consider incorporating these variables to enhance representativeness and to better understand how socio-demographic diversity shapes user acceptance of mobile banking technologies.

Furthermore, this research focused primarily on the antecedent components of the UTAUT model, whereas future work may examine outcome-based or longitudinal designs to better capture changes in user acceptance over time. Finally, predictive modeling techniques such as logistic regression or machine learning could be applied to classify users based on their actual adoption behavior, building upon the empirical dataset collected in this study.

Overall, this study gives practical advice to Thai banks and regulators seeking to enhance the secure and privacy-compliant deployment of biometric technologies under the PDPA framework, while also advancing theoretical integration between UTAUT and UTAUT2 within the context of biometric mobile banking.

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Author’s Contributions

Kriangsak Chanthinok: Responsible for the research planning and conceptual design, as well as drafting the initial manuscript.

Radyan Dananjoyo: Contributed to the refinement of the manuscript through academic English editing and approved the final version.

Palan Jantarajaturapath: Conducted the literature review in the relevant fields, designed the study, developed the research methodology, collected the data, and performed the data analysis.

Ethics

This research was conducted in accordance with the ethical standards for studies involving human participants. Ethical approval was obtained from the Mahasarakham University Ethics Committee for Research Involving Human Subjects under the approval number 186-123/2024. The research employed an expedited review process and was conducted at the Mahasarakham Business School (MBS), Mahasarakham University. All participants provided informed consent prior to their participation in the study.

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Appendix A:

Measurement Instrument: Questionnaire

Performance Expectancy (PE)

PE1 The mobile banking payment system is accurate.
PE2 The mobile banking payment system is convenient.
PE3 The mobile banking payment system operates quickly.

Effort Expectancy (EE)

EE1 The mobile banking payment system is easy to use.
EE2 The mobile banking payment system is flexible in transactions.
EE3 The mobile banking payment system is easy to learn.

Social Influence (SI)

SI1 Family, relatives, or friends help me use the mobile payment system.
SI2 Family, relatives, or friends recommend that I use face detection for mobile payments.
SI3 Family, relatives, or friends support my use of face detection for mobile payments.

Facilitating Conditions (FC)

FC1 Having a mobile device is essential for using mobile banking.
FC2 I have sufficient technological knowledge to use mobile banking.
FC3 My experience with other technologies helps me use mobile banking more effectively.

FC4 If there are issues with mobile banking, people around me can help resolve them.

Perceived Ease of Use (PEOU)

PEOU1 Using the mobile banking payment system is easy for me.
PEOU2 Face detection payments are easy to understand, and the steps are clear.
PEOU3 There are adequate tools to facilitate using the face detection payment system.

Perceived Usefulness (PU)

PU1 The mobile banking payment system allows me to make payments quickly.
PU2 Face detection payment systems are beneficial to me.
PU3 Face detection payment systems are safe for the account holder.

Attitude Toward Using (ATU)

ATU1 Using face detection payments is a good idea.
ATU2 Using face detection payments is a smart concept.
ATU3 I think most people who make purchases will use face detection to pay.

Intention to Use Face Detection on Mobile Banking (IFD)

IFD1 I intend to use facial scanning to confirm mobile banking payments in the future.
IFD2 I am happy to recommend others to use facial scanning mobile banking payment systems.
IFD3 I believe more people will use facial scanning to confirm mobile banking payments in the future.