Technology-Based Factors of University Students' Intentions to Use Ai-Enabled Mobile Banking: The Moderating Role of Personal Innovativeness

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A B S T R A C T

This study examines the technology based factors affecting university students' intents to embrace AI-enabled mobile banking in Sorong City, Southwest Papua, Indonesia. Employing a quantitative methodology, data were gathered from 159 students via surveys and analyzed using Structural Equation Modeling (SEM) with Partial Least Squares (PLS). The findings reveal that positive attitudes towards AI and perceived trust significantly effect the intention to use AI-enabled mobile banking. However, contrary to existing literature, relative advantage and security did not demonstrate significant relationships with intention to use Ai enabled- mobile banking. Personal innovativeness as moderating factor does not moderate the relationship between latent variables and the intention to use AI-enabled mobile banking. These findings suggest that students' perceptions of AI technologies differ from those in other contexts, underscoring the importance of tailored strategies by financial institutions. Despite AI's growing importance in mobile banking, limited research addresses its adoption determinants and the moderating role of personal innovativeness in underdeveloped regions like Sorong City. The study also adds to the body of knowledge on technology adoption in developing regions, which can inform mobile banking and AI integration research and practice.

1. Introduction

Smartphones have made online banking increasingly popular (Hussain et al., 2019)Artificial intelligence (AI) has rapidly changed financial services, especially mobile banking. AI-enabled mobile banking helps financial institutions personalize and streamline services to improve client experience and operations. PwC (PricewaterhouseCoopers) found that 82% of smartphone owners aged 18-24 utilize mobile banking (Noerlina et al., 2023). This study examines technology-based factors impacting university students' AI-enabled mobile banking aspirations in Sorong City, Southwest Papua, Indonesia.

1.1 Background

Mobile banking has progressed from SMS to artificial intelligence-driven applications. Traditional Indonesian mobile banking enables balance inquiries, financial transfers, and bill payments. Mobile banking with AI has transformed financial services. Chatbots, personalized recommendations, and fraud detection technologies have made mobile banking apps more effective. Mobile banking with AI has transformed financial services, chatbots, personalized recommendations, and fraud detection technologies have made mobile banking apps more effective *(Selcuk Koyluoglu & Emrah Acar, 2023)*. These advancements have generated interest in investigating the factors that influence user adoption and experienced use of AI-enabled mobile banking services, particularly among university students, considered as a young group who are considered more technologically literate. These AI-powered features increase user experience, security, and service customization. Bank Mandiri and Bank BRI have achieved considerable operational efficiency and customer satisfaction increases with AI integration.(Agustiawan, 2024)

Recent research has examined mobile banking AI adoption, including user acceptance, perceived usefulness and satisfaction(Lee et al., 2023). Foroughi et al., (2019) and Malaquias et al., (2018) also examined self-efficacy, channel choice, trust perception, convenience of use, and task characteristics connected to mobile banking to determine the intention to use. A better knowledge of the technology-based determinant factors that influence university students' intentions to utilize AI-enabled mobile banking services is crucial to be explored. The creation of the technology-based factors model was carried out by Payne et al., (2018), This research analyzes technology-based factors affecting digital natives' mobile banking and AI-enabled services. Key technological developments include: Attitudes toward AI, Relative advantage of mobile banking, security in specific mobile banking activities, Perceived trust in mobile banking. These factors will then be adapted by the author for analysis in research conducted on students who already use mobile banking in Sorong City. These factors will then be adapted by the author for analysis in research conducted on students who already use mobile banking in Sorong City. Understanding these determinants is urgently needed to help financial institutions design targeted strategies that enhance AI-driven mobile banking adoption, particularly in developing regions where digital transformation is critical for financial inclusion.

1.2 Problem Statement

While existing research has provided some insight into mobile banking adoption, there is a gap in understanding the technology-based factors that influence university students' intentions to use AI-enabled mobile banking, especially in developing regions like Sorong City. Personal innovativeness as a moderating factor also has not been deeply investigated. Additionally, the role of personal innovativeness as a moderating factor has not been thoroughly examined. Additionally, the inconsistencies in the results regarding the influence of relative advantage and security on adoption intentions underscore the necessity of conducting a more thorough examination of these variables in the context of AI-enabled mobile banking.

1.3 Objectives and Scope

As the scope is limited to university students in Sorong City, Southwest Papua, focusing on their perceptions of AI-enabled mobile banking applications, thus this study aims to:

1. The impact of AI-specific factors on mobile banking adoption intentions
2. The moderating role of personal innovativeness in AI-enabled mobile banking adoption
3. Develop a comprehensive model explaining adoption intentions using path analysis.

2. Literature Review

Mobile banking adoption has been extensively examined using various theoretical frameworks. This study maps relevant theories, including the Technology Acceptance Model

(TAM) and its extensions, to establish a robust theoretical foundation. The Technology Acceptance Model (TAM) has been widely used, perceived Usefulness and Ease of Use as two central constructs of TAM consistently emerging as significant predictors of adoption intentions (Li, 2023). Many researchers have used and modified TAM to describe customer behavior in information technology, including mobile banking. Some studies add trust, risk, service quality, and social elements to the TAM to boost its explanatory power (Susilowati & Auliah, 2023). Including technology-based factors specific to the context of Ai-enabled mobile banking service adoption which was initially started by Payne et al., (2018) is also an extension of the TAM model.

In the context of research with students as the subjects of analysis, research conducted in Indonesia has demonstrated that Muslim students' behavioral intentions to utilize mobile banking are influenced by facilitating conditions, social influence, and performance expectancy(Sudarsono et al., 2024). AI research in mobile banking is new but expanding. (Lee et al., 2023) discovered that perceived intelligence and anthropomorphism in AI features have a positive effect on user satisfaction and intention to keep using them. Trust has been identified as a critical factor in AI-enabled services adoption(Balakrishnan & Dwivedi, 2021).

2.1 Related Work

Akob & Sukarno (2022)evaluated the quality of mobile banking services in Indonesia and discovered that they had a positive impact on customer satisfaction and loyalty. This study gives information about the Indonesian context but does not directly address AI aspects. Nuangjamnong, (2021) investigated the factors that influence students' intentionin Bangkok metropolitan to utilize banking services via smartphones during the COVID-19 pandemic, highlighting convenience, relative advantage, and perceived utility. Although relevant to student populations, this study did not concentrate on AI-enabled features.

(Rokhimah & Suhermin, 2024)upgraded the Expectancy Confirmation Model (ECM) using AI factors for mobile banking in Southwest Papua. Their findings on AI's contribution in increasing user satisfaction and retention are particularly relevant to the current study.

2.2 Research Gap

These studies are helpful, but gaps remain:

1. AI-specific mobile banking adoption determinants are understudied, especially in underdeveloped countries like Sorong City.
2. Lack of research on how personal innovativeness moderates' university students' AI-enabled mobile banking usage.
3. Insufficient research on how technology-based factors (Positive Attitude towards AI, Relative Advantage, Security, and Perceived Trust) affect AI-enabled mobile banking adoption intentions.

3. Methodology

This chapter discusses the research strategy and methodology used to investigate university students' intentions to adopt AI-enabled mobile banking in Sorong City, Southwest Papua. Surveys and SEM with Partial Least Squares (PLS) are used in the quantitative research design. Similar technology adoption and mobile banking research use this approach. Multiple researchers choose PLS-SEM because it estimates complex models with multiple constructs, indicator variables, and structural routes without distributional assumptions (Hair et al., 2019).

3.1 Data Collection
3.1.1 Sample Method

The study relies on a survey of university students at University Muhammadiyah Sorong in Southwest Papua as its primary data source. As other field research, collecting data using convenience sampling used (Nuangjamnong, 2021; Rokhimah & Suhermin, 2024). Google Form questionnaires were sent electronically to 448 active Muhammadiyah University, Sorong Faculty of Economics students. This method is chosen for its efficiency and accessibility, especially considering the study's regional focus. Before filling out the questionnaire, students will be asked first whether they have actively used mobile banking in the last 6 months. If the answer is "Yes" then they are included in the sample criteria to be studied

Attitude towards AI, Relative Advantage, Security in specific mobile banking activities, Perceived Trust, Personal Innovativeness, and Intention to Use AI-enabled mobile banking will be used to create a structured questionnaire. The survey will use a 4-point Likert scale. The 4-point Likert Scale was chosen to minimize central tendency bias in 5-point scales for neutral options, as responders may choose the middle option because of confusion or statement rejection (Dolnicar, 2021). The survey will be administered online to maximize reach and convenience for the student population. In Table 1, the Operational Variable Matrix displays 26 indicator data for the Technology-based factors and Intention to Use variables.

Table 1. Operational Variable Matrix

Exogenous	Definition	Indicators	Measure Question	Scale	Source
Positive Attitudes towards AI	Attitude toward AI is the psychological disposition that individuals possess with respect to artificial intelligence technologies, which encompasses favorable perceptions.(Schepman & Rodway, 2023)	PA1. Perceived Utility PA2. Desired Use PA3. Positive Emotions (Schepman & Rodway, 2023)	1. AI improves efficiency and productivity in my work. 2. Willingness to incorporate AI into daily practices 3. Excitement about advancements and capabilities of AI.	1: Disageree 4: Strongly Agree	(Schepman & Rodway, 2023
Relative Advantages	Relative advantage is "the extent to which an innovation is perceived as superior to the concept it replaces." Emphasizing the comparative nature of relative advantage, this definition requires	RA1. Convenience RA2. Time Efficiency RA3. Accessibility RA4. User Control RA5. Enhanced Features	1. Mobile banking's ability to enhances user experience 2. Mobile banking allows users to complete transactions quickly 3. Ease of users to access mobile banking from various locations	1: Disageree 4: Strongly Agree	(Rogers, 1995) and (Payne et al., 2018)

Exogenous	Definition	Indicators	Measure Question	Scale	Source
	explicit comparisons between innovations (Rogers, 1995)	RA.6. Cost-Effectiveness. (Payne et al., 2018)	4. Mobile banking empowers users to manage their finances 5. Perceived benefits of AI-driven personalized services in mobile banking 6. Users perceive mobile banking as offering lower fees compared to other banking services		
Security in specific Mobile Banking	Consumers' responses to both perceived and actual online security threats, such as the hacking of their personal information, are referred to as perceived security (Yousafzai et al., 2010)	SMB1. Safe management Account SMB2. Secure Transaction SMB3. User Confidence SMB4. Perceived Security Measure on unauthorize access and data privacy(Apaua & Lallie, 2022; Payne et al., 2018; Suhartanto et al., 2022)	1. Confidence in safely checking account balance. 2. Perception of secure money transfers in mobile banking. 3. Security perception when paying bills via mobile banking. 4. Belief in protection against unauthorized account access. 5. Confidence in the privacy of financial data online	1: Disageree 4: Strongly Agree	(Yousafzai et al., 2010) (Apaua & Lallie, 2022; Payne et al., 2018; Suhartanto et al., 2022)

Exogenous	Definition	Indicators	Measure Question	Scale	Source
Perceived Trust	Trust is essential for any commercial relationship, and it is particularly important in online transactions as it mitigates uncertainty. (Al-Sharafi et al., 2018)	PT1. Institutional Trust PT2. Technology Trust PT3. Reliability PT4. Transparency PT5. Customer Support (Apaua & Lallie, 2022; Payne et al., 2018; Suhartanto et al., 2022)	1. Confidence in the banking institution's reputation, regulatory compliance 2. Trust in the technology behind mobile banking 3. mobile banking services performence reflecting users' expectations without errors 4. The openness regarding policies, fees, and security measures 5. The effectiveness and availability of customer service adressing issues	1: Disageree 4: Strongly Agree	(Al-Sharafi et al., 2018) (Apaua & Lallie, 2022; Payne et al., 2018; Suhartanto et al., 2022)
Personal Innovativeness	The willingness of an individual to experiment with any new information technology. (Agarwal & Prasad, 1998)	PI1. Willingness to Try New Technologies: PI2. Openness to Experimentation PI3. Complexity PI4. Trialability. (Senali et al., 2023; Tian et al., 2024)	1. The willingness to adopt new technology compare to their peers 2. How comfortable people are trying new tools or systems 3. How easy it is for users to understand and utilize the new technology 4. Allowing users to test the technology before adopting it	1: Disageree 4: Strongly Agree	(Agarwal & Prasad, 1998) (Senali et al., 2023; Tian et al., 2024)

Exogenous	Definition	Indicators	Measure Question	Scale	Source
Endogenous	**Definition**	**Indicator**		**Scale**	**Source**
Intention to Use AI-enabled mobile Banking (AIMB)	the willingness or propensity of users, to engage with mobile banking services that incorporate artificial intelligence.(Payne et al., 2018; Suhartanto et al., 2022)	IU1. AI Mobile Banking Future Intention IU2. Daily AI Mobile Banking Integration IU3. Frequency of Planned Usage(Giovanis et al., 2019)	1. Intend to use AI Mobile Banking in the future 2. Will use AI Mobile Banking in daily life 3. Plan to use AI Mobile Banking frequently	1: Disageree 4: Strongly Agree	(Payne et al., 2018; Suhartanto et al., 2022) (Giovanis et al., 2019)

Source: Processed by the Researcher (2024)

3.2 Analysis Techniques

3.2.1 Data anlysis Method

Data will be analyzed using SEM with PLS. This method is used for exploratory research and has the ability to handle complex models with various constructs(Hair et al., 2019) PLS-SEM is used to examine these interrelationships simultaneously and understand the elements that influence students' interest in AI-Enabled Mobile Banking, boosting methodological transparency and combining research aims with statistical methodologies. This PLS-SEM study examines direct and indirect effects between factors, giving financial companies actionable insights to improve financial services. For example, "Habit and trust on service provider also predicted intention, and facilitating conditions also had a direct effect on usage behavior when adopting digital banking in generation Z". (Rithmaya et al., 2024). This supports PLS-SEM's capacity to evaluate direct and indirect factor effects.

In data analysis, descriptive analysis comes initially to help to characterize respondents. Two steps of path model analysis evaluation follow. First examines convergent, discriminant, and convergent validity using the outer model. The second step tests the inner model using R2, F2, Q2, Path Coefficient, and T-Statistic. Calculation of path coefficients, R-squared values, and effect sizes will help determine the strength and significance of the relationships. This analytical method lets one thoroughly investigate the suggested model and hypotheses, consequently complementing the goals of the research.

3.2.2 Hypotheses Development

Other empirical studies can be used to form research hypotheses in addition to the literature connected to this research's title. Studies have consistently shown that positive attitudes towards AI, and perceived security as determinants of technology adoption (Stein et al., 2024; Thilagaraj A et al., 2024) In AI voice assistant studies, trust impacts intention to utilize AI technologies through perceived utility and attitudes (Choung et al., 2023). The concept of personal innovativeness has emerged as a critical moderating factor in technology adoption models. The intention to use technology was positively moderately affected by personal innovativeness in a meta-analysis of 29 impact sizes from 28 studies. This effect was constant across industries, technology kinds, age groups, and cultural contexts, showing its robustness as a technology adoption moderator (Ciftci et al., 2021). Studies on AI attitudes have also found that agreeableness and openness to experience positively associated with AI attitudes (Stein et al., 2024). Complements it all, to develop a hypothesis for the influence of variables related to relative advantage and security in specific mobile banking and perceived trust that can be predicted using previous research findings. In the context of mobile banking, perceived security increases trust and intention to use.

For instance, Study by Siagian et al., 2022) found that perceived security positively and significantly affects perceived trust in university electronic payment systems. Long before that, according to Flavián & Guinalíu, (2006), perceived security is a key factor in e-commerce adoption, since it is one of the three main aspects of website loyalty. van Deventer et al., (2017) found that relative advantage predicts mobile banking attitudes and usage, similarly with the research by (Payne et al., 2018)found that digital natives' mobile banking usage is primarily affected by relative advantage(van Deventer, 2022) revealed that trust significantly enhances Generation Y banking consumer's attitudes towards mobile banking, thereby improving their intention to utilize mobile banking services. Within the framework of Generation Z's adoption of digital banking, Kurniawan et al., (2023) discovered that intention to use digital banking was much influenced by trust in service providers. Collectively, these results offer a solid basis for examining the connections between attitudes, perceived relative advantages, security, trust, and the moderating influence of personal innovativeness in the adoption of AI-enabled mobile banking. In light of this literature, we made proposed the following hypotheses:

H1: Positive Attitude towards AI has a positive and significant relationship with intention to use AI-enabled mobile banking.
H2: Relative Advantage has a positive and significant relationship with intention to use AI-enabled mobile banking.
H3: Security in specific mobile banking activities has a positive and significant relationship with intention to use AI-enabled mobile banking.
H4: Perceived Trust has a positive and significant relationship with intention to use AI-enabled mobile banking.
H5: Personal Innovativeness positively moderates the relationship between Positive Attitude towards AI and intention to use AI-enabled mobile banking.
H6: Personal Innovativeness positively moderates the relationship between Relative Advantage and intention to use AI-enabled mobile banking.
H7: Personal Innovativeness positively moderates the relationship between Security and intention to use AI-enabled mobile banking.
H8: Personal Innovativeness positively moderates the relationship between Perceived Trust and intention to use AI-enabled mobile banking.

3.3 Validation

This study uses several comprehensive approaches in the validation procedure to guarantee data dependability and outcome credibility. The procedure starts with content validation by means of many literature reviews of past studies to build questionnaire relevance with the title, ensuring comprehensive construct coverage and regional relevance. A preliminary survey will be conducted with 30 students to test questionnaire clarity and effectiveness before full-scale implementation.

For construct validity, Confirmatory Factor Analysis (CFA) will assess whether measured variables adequately represent the theoretical constructs (Hair et al., 2019). For convergent validity, the measurement model will be examined using Average Variance Extracted (AVE) values (threshold > 0.5). Internal consistency reliability will be tested using Cronbach's alpha (threshold > 0.7) and composite reliability measures following PLS-SEM guidelines (Hair et al., 2019). To determine discriminant validity using the cross loadings method will be used, according to Chin (1998) the outer loading of each indicator on the related construct must be greater than the loading of that indicator on the other constructs (Rasoolimanesh, 2022).

4. Results and Discussion

4.1 Key Findings of the Research

4.1.1 Respondents' characteristics

The criteria for this study are students who have actively used mobile banking in the last 6 months and mobile banking that has been integrated with AI technology. According to various news sources on the website, BRI, Mandiri, BNI, BCA, and BSI are Indonesian mobile banking services that have used AI. Out of 171 questionnaires, 12 were damaged or due to respondents' data did not fulfill standards. Remaining 159 respondents' data will be processed. According to Hair et al., (2006), the minimal sample size is 5-10 times the estimated model coefficients. Using the 26 indicators planned for this research, the sample size is 130–260(Qosasi et al., 2019). Thus, the total of 159 samples collected in this study has satisfied the minimum requirements.

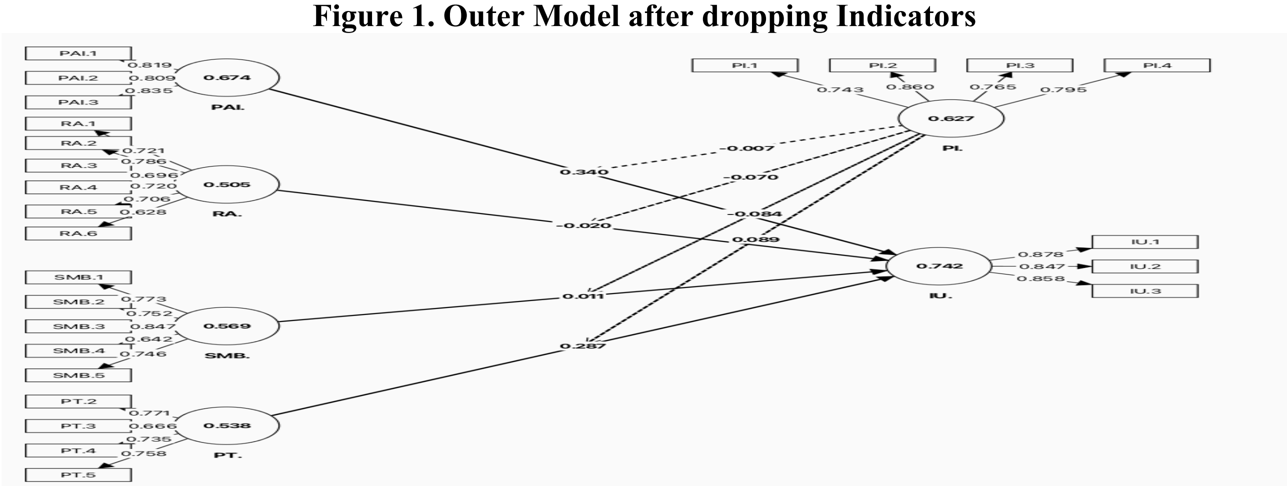
Most respondents participated in the survey were women (77%, 123), followed by men (23%, 36). The majority of students use several mobile banking services from banking institutions in Indonesia. Mobile Banking Bank BRI is utilized by 72% of 159 student respondents, followed by Bank Mandiri at 30%, BNI at 14%, BCA at 5%, and BSI at 1% of the total respondents. The study revealed that the dominant mobile banking features used by students are money transfer features, followed by bill payments for items (such as energy, credit, and water), account balance inquiries, and e-wallet balance top ups. These features are used by 60%-94% of student responses. Furthermore, it was discovered that 7% of the total student respondents use mobile banking for loan installment payments, while 3% have engaged in stock and investment product transactions using mobile banking.

4.1.2 Partial Least Square – Structural Equation Modeling (PLS-SEM) Analysis

(a) Outer Model-Loading Factor

A reflective indicator remains in place with an outer loading of 0.70. If outer loading is 0.40 to <0.70, researchers should consider dropping. Dropping is necessary for outer loading values of <0.40 (Hair et al., 2014). This research requires loading factor values and an Average Variance Extracted (AVE) value of > 0.50 for the latent variables Positive Attitudes towards AI, Relative Advantages, Security, and Perceived Trust. Low AVE values may indicate indicator loading troubles when indicators are not contributing to the construct they measure. If each indicator's loading is significantly below 0.5, researchers should eliminate it unless there is ideal theoretical justification (Hair et al., 2019)

Figure 1. Outer Model after dropping Indicators



Source: Smart PLS 4 Processed (2024)

According to Figure 1. above, the outer model analysis exhibits strong measurement qualities for all constructs following the refinement procedure. The Positive Attitude towards AI (PAI) construct demonstrates robust indicator loadings between 0.809 to 0.835, exceeding the 0.7 criterion suggested by Hair et al., (2017) for reliable construct measurement. The Relative Advantage (RA) construct exhibits appropriate loadings ranging from 0.628 to 0.786, whereas Security in Mobile Banking (SMB) shows acceptable loadings from 0.642 to 0.847, with the lower bound still exceeding the 0.4 threshold suggested by Hulland for exploratory research (Achjari, 2004). The Perceived Trust (PT) construct has good measurement quality, with loadings ranging from 0.666 to 0.771 following the dropping of the PT.1 indicator, as aresult personal innovativeness (PI) shows strong indicator loadings from 0.743 to 0.860. The removal of faulty indicators (PT.1) raised the model's Average Variance Extracted (AVE) above 0.50, ensuring convergent validity as prescribed by leading methodologists in structural equation modeling. This measuring method supports hypothesis testing and structural model evaluation, for this mobile banking adoption research.

(b) Convergent Validity Test

The table below shows this study model's Convergent Validity.

Table 2. Convergent Validity Result

Latent Variable	**Reflective Indicators**	**Convergent Validity Test**		**Status**
		Outer Loading	AVE	
Positive Attitude Towards Ai	PAI.1	0,819	0,674	VALID
	PAI.2	0,809		VALID
	PAI.3	0,835		VALID
Relative Advatage	RA.1	0,721	0,505	VALID
	RA.2	0,786		VALID
	RA.3	0,696		VALID
	RA.4	0,720		VALID
	RA.5	0,706		VALID
	RA.6	0,628		VALID
Security in Mobile Banking	SMB.1	0,773	0,569	VALID
	SMB.2	0,752		VALID
	SMB.3	0,847		VALID
	SMB.4	0,642		VALID
	SMB.5	0,746		VALID
Perceived Trust	PT.2	0,771	0,538	VALID
	PT.3	0,666		VALID
	PT.4	0,735		VALID
	PT.5	0,758		VALID
Personal Innovativeness	PI.1	0,743	0,627	VALID
	PI.2	0,860		VALID
	PI.3	0,765		VALID
	PI.4	0,795		VALID
Intention To Use	IU.1	0,878	0,742	VALID
	IU.2	0,847		VALID
	IU.3	0,858		VALID

Source: Smart PLS 4 Processed (2024)

The AVE has satisfied the minimum criteria, as indicated in the table above. According to (Ghozali, 2014), the Average Variance Extracted (AVE) is considered legitimate when the AVE of each latent variable exceeds 0.5. Convergent validity is established as each latent variable

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possesses an AVE value exceeding 0.5, signifying that it accurately represents indicators and measures constructs.

(c) Discriminant Validity Test

The cross-loading value discriminant validity test results are given here:

Table 3. Cross-Loading Result

	IU.	PAI.	PI.	PT.	RA.	SMB.
IU.1	**0,878**	0,525	0,442	0,405	0,148	0,357
IU.2	**0,847**	0,377	0,415	0,457	0,247	0,404
IU.3	**0,858**	0,422	0,465	0,381	0,293	0,311
PAI.1	0,378	**0,819**	0,229	0,128	0,236	0,335
PAI.2	0,355	**0,809**	0,286	0,269	0,138	0,280
PAI.3	0,507	**0,835**	0,403	0,245	0,258	0,319
PI.1	0,299	0,231	**0,743**	0,349	0,217	0,310
PI.2	0,533	0,310	**0,860**	0,518	0,372	0,466
PI.3	0,260	0,204	**0,765**	0,436	0,290	0,428
PI.4	0,428	0,423	**0,795**	0,466	0,274	0,369
PT.2	0,394	0,170	0,496	**0,771**	0,249	0,508
PT.3	0,303	0,185	0,472	**0,666**	0,259	0,448
PT.4	0,331	0,154	0,303	**0,735**	0,210	0,328
PT.5	0,372	0,260	0,396	**0,758**	0,204	0,323
RA.1	0,189	0,175	0,139	0,173	**0,721**	0,252
RA.2	0,213	0,280	0,291	0,210	**0,786**	0,342
RA.3	0,180	0,085	0,242	0,196	**0,696**	0,247
RA.4	0,189	0,127	0,307	0,250	**0,720**	0,279
RA.5	0,214	0,300	0,368	0,288	**0,706**	0,363
RA.6	0,099	0,087	0,227	0,216	**0,628**	0,255
SMB.1	0,304	0,333	0,311	0,422	0,288	**0,773**
SMB.2	0,261	0,274	0,351	0,349	0,338	**0,752**
SMB.3	0,426	0,331	0,386	0,454	0,266	**0,847**
SMB.4	0,183	0,177	0,421	0,389	0,314	**0,642**
SMB.5	0,313	0,281	0,461	0,453	0,397	**0,746**

Source: Smart PLS 4 Processed (2024)

Barclay et al. (1995) and Chin (1998) were the pioneers in formally asserting that the loading of each indicator must exceed all of its cross-loadings to validate discriminant validity (Henseler et al., 2015). This established a common criterion whereby an item must exhibit greater loadings on its parent construct than on other constructs within the research. Based on the results of the table above, discriminant validity is generally supported, as the majority of indicators have more load on their designated constructs than on others. For example, PAI.1 to PAI.3 exhibit a significant load on PAI (0.809–0.835), while cross-loadings on other constructs are significantly lower. This gives proof to the PAI construct's distinctiveness. Likewise, other construct variables in the preceding table have greater values within their variables, showing discriminant validity. These findings demonstrate that the components are well-defined and that the model has discriminant validity, allowing accurate interpretation of each latent variable's unique contribution to users' intention to embrace AI-enabled mobile banking.

(d) Reliability Test

Table 4. Composite Realibility Result

	Cronbach's alpha	Composite reliability (rho_c)
IU.	0,826	0,896
PAI.	0,764	0,861
PI.	0,807	0,870
PT.	0,714	0,823
RA.	0,806	0,859
SMB.	0,814	0,868

Source: Smart PLS 4 Processed (2024)

The reliability outcomes presented in the above table demonstrate that the constructs in this study satisfy the reliability criteria for both Cronbach's alpha and Composite Reliability. A reliability outcome is deemed acceptable if Cronbach's alpha exceeds 0.60 and satisfactory if it surpasses 0.70(Hair et al., 2019). The results affirm the validity of the measuring model and indicate that the indicators effectively represent their respective constructs.

4.2 Interpretation of Results

4.2.1 Structural Evaluation Examination (inner Model)

Table 5. Coefficient of Determination

	R-square	R-square adjusted
Intention to Use	0,440	0,406

Source: Smart PLS 4 Processed (2024)

The model explains 44% of users' Intention to Use AI-enabled mobile banking, with an adjusted R-square of 0.406 (40.6%). This suggests that the model has moderate explanatory power, since Positive Attitude towards AI (PAI), Relative Advantage (RA), Security in Mobile Banking (SMB), and Perceived Trust (PT) explain for about half of the variation in adoption intentions. The R-square values of 0.67, 0.33, and 0.19 are strong, moderate, and weak, according to Chin (1998). R-squared values of 0.75, 0.50, and 0.25 are substantial, moderate, and weak, according to Hair et al., (2019).

4.2.2 Path Coefficient and Hypotheses Results

A comprehensive Structural Analysis Model analysis is below:

Table 6. Structural Analysis Model Results

Hypothesis	Connection	Path coefficient			Status	Decision
		Sample	T-stat	P-val		
H1	Positive Attitude -> Intention to Use Ai-Enabled Mobile Banking	0,340	4,060	0,000	Significant	Accepted
H2	Relative Advantage-> Intention to Use Ai-Enabled Mobile Banking	-0,020	0,287	0,774	Not Significant	Rejected
H3	Security -> Intention to Use Ai-Enabled Mobile Banking	0,011	0,120	0,905	Not Significant	Rejected

H4	Perceived Trust -> Intention to Use Ai-Enabled Mobile Banking	0,287	3,637	0,000	Significant	Accepted
H5	Positive Attitude x Personal Innovativeness -> Intention to Use Ai-Enabled Mobile Banking	-0,007	0,075	0,940	Not Significant	Rejected
H6	Relative Advantage x Personal Innovativeness -> Intention to Use Ai-Enabled Mobile Banking	-0,070	0,961	0,337	Not Significant	Rejected
H7	Security x Personal Innovativeness -> Intention to Use Ai-Enabled Mobile Banking	-0,084	0,711	-0,084	Not Significant	Rejected
H8	Perceived Trust x Personal Innovativeness -> Intention to Use Ai-Enabled Mobile Banking	0,089	0,915	0,360	Not Significant	Rejected
Additional finding	Personal Innovativeness -> Intention to Use Ai-Enabled Mobile Banking	0,207	2,368	0,018	Significant	
F^2	Positive Attitude towards Ai				0,163	
	Personal Innovativeness				0,042	
	Perceived Trust				0,077	
Q^2			0,290			

Source: Smart PLS 4 Processed (2024)

The hypothesis testing results examine the links between Positive Attitude, Relative Advantage, Security, Perceived Trust, and Personal Innovativeness and AI-Enabled Mobile Banking Intention to use. Each hypothesis is detailed below:

Accepted Hypotheses

H1: Positive Attitude towards AI→ Intention to Use AI-Enabled Mobile Banking

The path coefficient is 0.340, the T-statistic of 4.060, and the P-value of 0.000, $p<0.001$ support this hypothesis. These findings demonstrate that a positive attitude towards AI strongly promotes AI-enabled mobile banking adoption. Positive Attitude plays a significant role in shaping user intentions, as indicated by the moderate impact size ($f^2 = 0.163$).

H4: Perceived Trust → Intention to Use AI-Enabled Mobile Banking

The path coefficient is 0.287, the T-statistic of 3.637, and the P-value of 0.000, $p<0.001$ support this hypothesis. These findings support the literature on trust in digital and AI-driven services by showing that trust shapes user intentions. Small yet significant effect size of perceived trust is indicated by the f^2 value of 0.077.

Rejected Hypotheses

H2: Relative Advantage → Intention to Use AI-Enabled Mobile Banking

The path coefficient is -0.020, the T-statistic is 0.287, and the P-value is 0.774, $p>0.001$ reject this hypothesis. These data imply that Relative Advantage does not significantly affect customers' intention to adopt AI-enabled mobile banking.

H3: Security → Intention to Use AI-Enabled Mobile Banking

The path coefficient is 0.011, the T-statistic is 0.120, and the P-value is 0.905, $p>0.001$ reject this hypothesis. This suggests that mobile banking consumers' intention is unaffected by security in specific mobile banking. This suggests that mobile banking consumers' interest is unaffected by perceived security.

Moderating Effects

All moderating hypotheses (H5-H8) involving Personal Innovativeness were rejected.

H5: Positive Attitude × Personal Innovativeness → Intention to Use AI-Enabled Mobile Banking

The path coefficient is -0.007, the T-statistic is 0.075, and the P-value is 0.940, $p>0.001$ reject this hypothesis. Indicating that users' individual innovativeness may not moderate the impact of their positive attitudes towards Ai.

H6: Relative Advantage × Personal Innovativeness → Intention to Use AI-Enabled Mobile Banking

The path coefficient is -0.070, the T-statistic is 0.961, and the P-value is 0.337, $p>0.001$ reject this hypothesis. Indicating Personal Innovativeness does not moderate the influence of perceived Relative Advantage on the intention to use AI-enabled mobile banking.

H7: Security × Personal Innovativeness → Intention to Use AI-Enabled Mobile Banking

The path coefficient is -0.084, the T-statistic of 0.711, and the P-value of 0.084, $p>0.001$ reject this hypothesis. Personal Innovativeness does not moderate the relationship between Security and Intention to Use, indicating that innovativeness does not affect security perceptions in mobile banking.

H8: Perceived Trust × Personal Innovativeness → Intention to Use AI-Enabled Mobile Banking

The path coefficient is 0.089, the T-statistic is 0.915, and the P-value is 0.360, $p>0.001$ reject this hypothesis. Personal Innovativeness does not significantly moderate the relationship between Perceived Trust and Intention to Use, suggesting trust alone is more important.

Additional Findings

Personal innovativeness significantly impacts the intention to use AI-enabled mobile banking, evidenced by a path coefficient of 0.207, a T-statistic of 2.368, and a P-value of 0.018, however it does not serve as an effective moderator, this suggests that users exhibiting greater innovativeness are more likely to embrace the technology.

Predictive Relevance (Q^2) and Effect Sizes (f^2)

The Q^2 value of 0.290 indicates that the model possesses substantial predictive relevance for Intention to Use. Positive Attitude ($f^2 = 0.163$) exhibits the most significant effect size, followed by Perceived Trust ($f^2 = 0.077$). Personal Innovativeness ($f^2 = 0.042$) impacts a small yet significant effect. (Hair et al., 2017) assert that Q^2 values above zero indicate effective reconstruction of values and demonstrate the model's predictive relevance. Cohen (1988) established generally recognized standards indicating that f^2 values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively.

5. Discussion

This research investigated the determinants affecting university students' intentions to use AI-enabled mobile banking in Sorong City, Southwest Papua, Indonesia. The results offer significant understanding of the technology's adoption by digital natives in a developing region. This Study found a significant relationship between positive AI attitudes and intention to use AI-based mobile banking ($\beta = 0.340$, $p < 0.001$). According to the Diffusion of Innovation Theory (Rogers, 1995)

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a positive attitude toward a technological innovation promotes it dissemination. Additionally, perceived trust significantly influences usage intention ($\beta = 0.287$, $p < 0.001$), supporting the Trust and Commitment Theory in marketing (Morgan & Hunt, 1994).

Contrary to some earlier research, relative advantage and security did not influence usage intention. This may be explained by Institutional Theory by DiMaggio & Powell (1983) which highlights the importance of contextual factors and social norms in technology adoption. Considering Sorong's student population, other elements might be more important than relative advantage and perceived security. The role of personal innovativeness as a moderator was also not proven to be significant, which challenges the assumption of the Theory of Individual Characteristics in Technology Innovation Adoption (Agarwal & Prasad, 1998).These findings suggest that in the context. of AI-based mobile banking in developing regions, situational factors may play a bigger role than individual characteristics.

5.1 Comparison with Prior Research

Positive Attitude towards AI

Our findings indicate that the intention to use AI-enabled mobile banking is significantly affected by a positive attitude toward AI. This is consistent with prior research as previously discussed in this research's literature review. A study done by Suhartanto et al., (2022), and (Lee et al., 2023) discovered that technology adoption was significantly influenced by positive attitudes toward AI. Our results extend this to the specific context of AI-enabled mobile banking among university students in Indonesia.

Perceived Trust

The research supports the critical role of perceived trust in determining intentions to utilize AI-enabled mobile banking. This is in accordance with the findings of Balakrishnan & Dwivedi (2021), who identified trust as a critical factor in the adoption of technology continuance. Similarly,van Deventer (2022) discovered that Generation Y banking consumers' attitudes toward mobile banking are significantly influenced by trust. These findings are further supported by our findings in the context of Indonesian university students.

Personal Innovativeness

Although our research demonstrated that personal innovativeness has a direct impact on intention to use, it did not function as an effective moderator. This partially contradicts the findings of Ciftci et al., (2021), who discovered that personal innovativeness is a robust moderator in a variety of contexts. Our results indicate that innovativeness may have a more direct impact in the specific context of AI-enabled mobile banking among Indonesian students.

Relative Advantage and Security

In contrast to many prior studies, our research did not identify significant correlations between relative advantage or security and the intention to use. This contrasts with the findings of Mousavian & Abbasi (2021) and Payne et al., (2018), who identified relative advantage as a significant predictor of mobile banking adoption. Our findings on security similarly contradict the research conducted by Siagian et al., (2022) which indicated that perceived security positively influences trust in electronic payment systems.

5.2 Limitations

Several limitations must be considered when analyzing the findings of this study:

1. Geographic Scope: The research was limited to university students in Sorong City, potentially lacking representation of the wider Indonesian population or other developing regions.
2. Sample Characteristics: The sample was primarily female (77%), which may bias the results if gender disparities exist in the adoption of AI-enabled mobile banking.
3. Self-reported Data: Dependence on self-reported data may create bias, as respondents might not accurately represent their beliefs or intentions.
4. Limited AI Focus: While the study examined AI-enabled mobile banking, it did not discuss deeply into specific AI features or functionalities, which could provide more nuanced insights.

5.3 Future Research

Our findings and limitations suggest multiple directions for future investigation:

1. Longitudinal Studies: Execute longitudinal studies to monitor the evolution of attitudes and adoption behaviors over time as AI-enabled mobile banking gains prevalence
2. Elaborated Geographic Scope: Broaden the study to encompass additional locations in Indonesia and analyze outcomes across diverse cultural and economic contexts within the nation.
3. Examine the influence of particular AI functionalities (e.g., chatbots, tailored suggestions) on adoption intentions and user satisfaction.
4. Behavioral Outcomes: Broaden the research to investigate actual usage behavior alongside adoption objectives
5. Comparative Analysis: Examine the adoption determinants of AI-enabled versus traditional mobile banking services to discern distinctive elements of AI adoption.

6. Conclusion

This study examined how technology affects university students' aspirations to adopt AI-enabled mobile banking in Sorong City, Southwest Papua, Indonesia. The study sought to fill a gap in the literature on AI acceptance in mobile banking, particularly among youthful, tech-savvy developing nations.

A quantitative technique was used to examine data from 159 university students who utilize mobile banking services utilizing surveys and SEM with PLS. Positive attitudes towards AI and perceived trust strongly affect the desire to utilize AI-enabled mobile banking. Contrary to prior studies, relative advantage and security did not significantly affect adoption intentions, suggesting user perceptions may vary in this population.

This work has significant implications for financial organizations seeking to improve their AI-driven mobile banking services. By comprehending the principal factors influencing adoption among university students, banks can customize their methods to enhance user experience and increase client engagement. This research enhances the area by offering empirical information regarding the specific characteristics that affect technology adoption within a distinct cultural setting, hence expanding the current body of information on mobile banking and AI technologies.

7. Recommendation

This study's findings yield many recommendations for stakeholders in the financial services sector and for subsequent research endeavors:

1. Enhance User Education: Emphasizing the potential of these technologies to enhance user experience may cultivate positive attitudes toward their adoption.
2. Build Trust: Since perceived trust significantly impacts adoption intentions, banks must develop strategies to improve transparency and security in their AI systems. Regular communication about security protocols and user data protection can help build trust among users.

3. Subsequent Investigations: Future research should examine the factors contributing to the insignificance of relative advantage and security in this environment. Furthermore, longitudinal research may elucidate the evolution of attitudes and actions as consumers gain familiarity with AI technologies over time.

Appendix

The questionnaire used in this study was distributed using Google Forms, which can be accessed at the following link :
https://docs.google.com/forms/d/e/1FAIpQLSchFyJ6x37xHsTiwWHRLT8aS22jL4kOsAQ_jzH5hNnJLynyxA/viewform?usp=sharing

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REFERENCES

[1] Achjari, D. (2004). PARTIAL LEAST SQUARES: ANOTHER METHOD OF STRUCTURAL EQUATION MODELING ANALYSIS. In *Jurnal Ekonomi dan Bisnis Indonesia* (Vol. 19, Issue 3).

[2] Agarwal, R., & Prasad, J. (1998). A Conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology. *Information Systems Research*, *9*(2), 204–215. https://doi.org/10.1287/isre.9.2.204

[3] Agustiawan, D. A. (2024). Digital Banking Transformation AI Enhances Efficiency And Customer Experience Seminar Perspective Industry. *WACANA: Jurnal Ilmiah Ilmu Komunikasi*, *23*(1), 191–200. https://doi.org/10.32509/wacana.v23i1.4130

[4] Akob, R. A., & Sukarno, Z. (2022). Pengaruh Kualitas Layanan Mobile Banking terhadap Kepuasan dan Loyalitas Nasabah Bank BUMN di Makassar. *Jurnal Maksipreneur: Manajemen, Koperasi, Dan Entrepreneurship*, *11*(2), 269. https://doi.org/10.30588/jmp.v11i2.889

[5] Al-Sharafi, M. A., Arshah, R. A., Alajmi, Q., Herzallah, F. A., & Qasem, Y. A. M. (2018). The Influence of Trust in Consumer Perception to Accept Internet Banking Services: An Empirical Evidence. *Indian Journal of Science and Technology*, *11*(20), 1–9. https://doi.org/10.17485/ijst/2018/v11i20/91928

[6] Apaua, R., & Lallie, H. S. (2022). Measuring User Perceived Security of Mobile Banking Applications. *ArXiv, Abs/2201.03052.*

[7] Balakrishnan, J., & Dwivedi, Y. K. (2021). Role of cognitive absorption in building user trust and experience. *Psychology & Marketing*, *38*(4), 643–668. https://doi.org/10.1002/mar.21462

[8] Choung, H., David, P., & Ross, A. (2023). Trust in AI and Its Role in the Acceptance of AI Technologies. *International Journal of Human–Computer Interaction*, *39*(9), 1727–1739. https://doi.org/10.1080/10447318.2022.2050543

[9] Ciftci, O., Berezina, K., & Kang, M. (2021). Effect of Personal Innovativeness on Technology Adoption in Hospitality and Tourism: Meta-analysis. In *Information and Communication Technologies in Tourism 2021* (pp. 162–174). Springer International Publishing. https://doi.org/10.1007/978-3-030-65785-7_14

[10] Cohen, J. (2013). *Statistical Power Analysis for the Behavioral Sciences*. Routledge. https://doi.org/10.4324/9780203771587
[11] DiMaggio, P. J., & Powell, W. W. (1983). The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. *American Sociological Review*, *48*(2), 147. https://doi.org/10.2307/2095101
[12] Dolnicar, S. (2021). 5/7-point “Likert scales” aren’t always the best option. *Annals of Tourism Research*, *91*, 103297. https://doi.org/10.1016/j.annals.2021.103297
[13] Flavián, C., & Guinalíu, M. (2006). Consumer trust, perceived security and privacy policy. *Industrial Management & Data Systems*, *106*(5), 601–620. https://doi.org/10.1108/02635570610666403
[14] Foroughi, B., Iranmanesh, M., & Hyun, S. S. (2019). Understanding the determinants of mobile banking continuance usage intention. *Journal of Enterprise Information Management*, *32*(6), 1015–1033. https://doi.org/10.1108/JEIM-10-2018-0237
[15] Ghozali. (2014). *Patrial Least Squares Konsep, Teknik Dan Aplikasi Menggunakan Program Smart Pls 3.0 Untuk Penelitian Empiris*. Universitas Diponegoro.
[16] Giovanis, A., Assimakopoulos, C., & Sarmaniotis, C. (2019). Adoption of mobile self-service retail banking technologies: The role of technology, social, channel and personal factors. *International Journal of Retail and Distribution Management*, *47*(9), 894–914. https://doi.org/10.1108/IJRDM-05-2018-0089
[17] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
[18] Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. In *European Business Review* (Vol. 26, Issue 2, pp. 106–121). Emerald Group Publishing Ltd. https://doi.org/10.1108/EBR-10-2013-0128
[19] Hair, J. F., Tomas, G., Hult, M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) Second Edition*. http://study.sagepub.com/
[20] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
[21] Hussain, S., Qazi, S., Ahmed, R. R., Vveinhardt, J., & Streimikiene, D. (2019). Innovative user engagement and playfulness on adoption intentions of technological products: evidence from SEM-based multivariate approach. *Economic Research-Ekonomska Istraživanja*, *32*(1), 555–577. https://doi.org/10.1080/1331677X.2018.1558086
[22] Kurniawan, Y., Dumais, S. M., & Anwar, N. (2023). An Empirical Study on the Factors Affecting the Usage of Digital Banking in Generation Z. *Journal of System and Management Sciences*, *13*(5). https://doi.org/10.33168/JSMS.2023.0503
[23] Lee, J. C., Tang, Y., & Jiang, S. Q. (2023). Understanding continuance intention of artificial intelligence (AI)-enabled mobile banking applications: an extension of AI characteristics to an expectation confirmation model. *Humanities and Social Sciences Communications*, *10*(1). https://doi.org/10.1057/s41599-023-01845-1
[24] Li, K. (2023). Determinants of College Students’ Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model. *Sustainability*, *15*(6), 5221. https://doi.org/10.3390/su15065221
[25] Malaquias, F., Malaquias, R., & Hwang, Y. (2018). Understanding the determinants of mobile banking adoption: A longitudinal study in Brazil. *Electronic Commerce Research and Applications*, *30*, 1–7. https://doi.org/10.1016/j.elerap.2018.05.002

[26] Morgan, R. M., & Hunt, S. D. (1994). The Commitment-Trust Theory of Relationship Marketing. *Journal of Marketing*, *58*(3), 20. https://doi.org/10.2307/1252308

[27] Mousavian, S. J., & Abbasi, H. (2021). Factors Influencing Mobile Banking Adoption in Iranian Clients. In *Jurnal Bisnis dan Kewirausahaan (Journal of Business and Entrepreneurship)* (Vol. 9, Issue 1).

[28] Noerlina, N., Freda, D. C., Mayo, G., Tirtawijaya, Y. K., & Samuel, J. (2023). The Future Prospect of Mobile Banking Technology Enhancement in Indonesia. *Business Economic, Communication, and Social Sciences Journal (BECOSS)*, *5*(1), 25–34. https://doi.org/10.21512/becossjournal.v5i1.8743

[29] Nuangjamnong, C. (2021). Investigation of Factors Influencing Students' Intention to Use Banking Services through Smartphone Devices during COVID-19 Pandemic. *International Journal of Economics and Business Administration*, *IX*(Issue 1), 331–346. https://doi.org/10.35808/ijeba/676

[30] Payne, E. M., Peltier, J. W., & Barger, V. A. (2018). Mobile banking and AI-enabled mobile banking: The differential effects of technological and non-technological factors on digital natives' perceptions and behavior. *Journal of Research in Interactive Marketing*, *12*(3), 328–346. https://doi.org/10.1108/JRIM-07-2018-0087

[31] Qosasi, A., Maulina, E., Purnomo, M., Muftiadi, A., Permana, E., & Febrian, F. (2019). The impact of Information and Communication Technology capability on the competitive advantage of small businesses. *International Journal of Technology*, *10*(1), 167–177. https://doi.org/10.14716/ijtech.v10i1.2332

[32] Rasoolimanesh, S. M. (2022). Discriminant validity assessment in PLS-SEM: A comprehensive composite-based approach. In *Data Analysis Perspectives Journal* (Vol. 3, Issue 2). https://www.scriptwarp.com,

[33] Rithmaya, C. L., Ardianto, H., & Sistiyarini, E. (2024). GEN Z AND THE FUTURE OF BANKING: AN ANALYSIS OF DIGITAL BANKING ADOPTION. *Jurnal Manajemen Dan Kewirausahaan*, *26*(1), 64–78. https://doi.org/10.9744/jmk.26.1.64-78

[34] Rogers, E. M. (1995). Diffusion of Innovations: Modifications of a Model for Telecommunications. In *Die Diffusion von Innovationen in der Telekommunikation* (pp. 25–38). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-79868-9_2

[35] Rokhimah, R., & Suhermin, S. (2024). FACTORS INFLUENCING CONTINUATION INTENTION OF MOBILE BANKING USAGE: EXTENDING EXPECTANCY CONFIRMATION MODEL (ECM) AND ARTIFICIAL INTELLIGENCE (AI) WITH SECURITY AS MODERATION. *International Conference of Business and Social Sciences*, 162–178. https://doi.org/10.24034/icobuss.v4i1.493

[36] Schepman, A., & Rodway, P. (2023). The General Attitudes towards Artificial Intelligence Scale (GAAIS): Confirmatory Validation and Associations with Personality, Corporate Distrust, and General Trust. *International Journal of Human-Computer Interaction*, *39*(13), 2724–2741. https://doi.org/10.1080/10447318.2022.2085400

[37] Selcuk Koyluoglu, A., & Emrah Acar, O. (2023). A STUDY ON ADOPTION OF ARTIFICIAL INTELLIGENCE USE IN MOBILE BANKING. *EMC Review - Časopis Za Ekonomiju - APEIRON*, *26*(2). https://doi.org/10.7251/EMC2302344K

[38] Senali, M. G., Iranmanesh, M., Ismail, F. N., Rahim, N. F. A., Khoshkam, M., & Mirzaei, M. (2023). Determinants of Intention to Use e-Wallet: Personal Innovativeness and Propensity to Trust as Moderators. *International Journal of Human-Computer Interaction*, *39*(12), 2361–2373. https://doi.org/10.1080/10447318.2022.2076309

[39] Siagian, H., Tarigan, Z. J. H., Basana, S. R., & Basuki, R. (2022). The effect of perceived security, perceived ease of use, and perceived usefulness on consumer behavioral intention

through trust in digital payment platform. *International Journal of Data and Network Science*, *6*(3), 861–874. https://doi.org/10.5267/j.ijdns.2022.2.010

[40] Stein, J.-P., Messingschlager, T., Gnambs, T., Hutmacher, F., & Appel, M. (2024). Attitudes towards AI: measurement and associations with personality. *Scientific Reports*, *14*(1), 2909. https://doi.org/10.1038/s41598-024-53335-2

[41] Sudarsono, H., Utami, S., Rahmi, A. N., Yuniarti, F. R., & Suciningtias, S. A. (2024). Exploring Muslim students' adoption of mobile banking in conventional banks. *Asian Journal of Islamic Management (AJIM)*, 23–34. https://doi.org/10.20885/AJIM.vol6.iss1.art3

[42] Suhartanto, D., Syarief, M. E., Chandra Nugraha, A., Suhaeni, T., Masthura, A., & Amin, H. (2022). Millennial loyalty towards artificial intelligence-enabled mobile banking: evidence from Indonesian Islamic banks. *Journal of Islamic Marketing*, *13*(9), 1958–1972. https://doi.org/10.1108/JIMA-12-2020-0380

[43] Susilowati, E., & Auliah, A. N. (2023). Factors Affecting Students' Use of Mobile Banking: An Extension of Technology Acceptance Model. *Journal of Accounting and Strategic Finance*, *6*(1), 16–34. https://doi.org/10.33005/jasf.v6i1.387

[44] Thilagaraj A, D. R., Davis K, J., Sairam, S., & Selvakumar, R. (2024). Migration Letters The Artificial Intelligence Revolution: Transforming Mobile Banking Applications And Adoption. *Migration Letters*, *21*(S6), 91–99. www.migrationletters.com

[45] Tian, Y., Chan, T. J., Liew, T. W., Chen, M. H., & Liu, H. N. (2024). Does personal innovativeness and personal anxiety matter? The predictors of continuance use intention of an e-wallet system. *Kybernetes*. https://doi.org/10.1108/K-10-2023-2213

[46] van Deventer, M. (2022). Mobile banking behavioral usage intention among South African Generation Y consumers. *Banks and Bank Systems*, *17*(3), 129–141. https://doi.org/10.21511/bbs.17(3).2022.11

[47] van Deventer, M., de Klerk, N., & Bevan-Dye, A. (2017). Antecedents of attitudes towards and usage behavior of mobile banking amongst Generation Y students. *Banks and Bank Systems*, *12*(2), 78–90. https://doi.org/10.21511/bbs.12(2).2017.08

[48] Yousafzai, S. Y., Foxall, G. R., & Pallister, J. G. (2010). *Explaining Internet Banking Behavior: Theory of Reasoned Action, Theory of Planned Behavior, or Technology Acceptance Model? 1*.