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CONSUMER BEHAVIOR | RESEARCH ARTICLE

Determinants of AI Innovation Adoption in Banking Services: Mediating Role of Attitude among Young Generations

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Abstract:

Background: Integration of AI technology in the banking sector is growing rapidly, but adoption remains relatively low due to users' concerns regarding awareness, privacy, and security. This situation necessitated the exploration of how an expanded version of the Technology Acceptance Model (TAM) model influenced AI adoption, particularly among younger generations.
Purpose: This research aimed to examine how awareness, perceived security, and ease of use could directly influence AI adoption through attitude as a mediator.
Method: A quantitative survey was carried out among 418 bank customers from BCA, BNI, BRI, Mandiri, and OCBC in Indonesia who had used AI-based banking services, and the data were analyzed using PLS-SEM.
Findings: Awareness, perceived security, and ease of use strongly influenced the intention to adopt AI, both directly and through a mediating effect. Furthermore, Generation Y was more affected by ease of use and security than Generation Z.
Conclusions: All variables were found to significantly influence the willingness to adopt AI, with attitude serving as a mediating factor.
Research implication: This research strengthened the TAM model by integrating ease of use, security, and awareness variables, as well as focusing on generational differences in technology adoption.

Keywords: AI-based banking, artificial intelligence, generation Z, generation Y, intention to adopt AI, technology acceptance model (TAM)

JEL Classification: G21, O33, M31

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PUBLIC INTEREST STATEMENT

This study addresses a key challenge: even though AI integration in the banking sector is rapidly growing, adoption among users remains relatively low. For customers, the barriers are strongly linked to limited awareness of AI-based banking services, as many users may not fully understand what AI can offer or how it works. In addition, adoption is hindered by concerns about privacy and security, since customers may worry about how their data is collected, stored, or protected. Another challenge involves the perceived ease of use of AI services—whether customers find them simple, intuitive, and convenient enough to use without difficulty. Furthermore, the research highlights the need to understand generational differences, because Generation Y and Generation Z may evaluate AI differently, particularly in terms of how they respond to ease and security. Overall, this study aims to provide evidence-based insights into the factors that reduce these adoption barriers, helping banks design AI solutions that are more trusted, secure, and user-friendly.

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1. Introduction

The implementation of AI-based services in the world banking sector is rising rapidly as more daily activities shift online and operational efficiency becomes increasingly essential. In 2023, the AI world market in banking was worth $19.87B and projected to reach $143.56B in 2030, with a Compound Annual Growth Rate (CAGR) of 31.8% (Grand View Research, 2024). AI improves banking efficiency through fraud detection, personalized services, and risk management. According to previous research, digital transformation has made AI an automation tool and a strategic base for businesses to add value and become more productive (McKinsey & Company et al., 2024).

In Indonesia, the banking sector is further adopting AI due to the government's encouragement of digital transformation. The Financial Services Authority (OJK) pointed out that using AI technology is particularly important to make the national banking system more competitive, efficient, and high-quality (Otoritas Jasa Keuangan, 2025). The growth of financial technology has helped Indonesia's financial inclusion rate, which is now approximately 84% (World Economic Forum, 2025). However, users still face concerns regarding AI-based banking services. Concerns about privacy and security are the top priorities that affect individual's decisions to adopt. Research shows that less than 30% of users trust AI chatbots for financial guidance, while half believe AI can improve financial situation (Banking Dive, 2024).

Beyond user perceptions, generational differences affect willingness to use AI technology. As digital natives, Generation Z tends to adopt AI more readily than Generation Y despite concerns about data privacy (Digital Future Society, 2024; Kumparan, 2025; McKinsey, 2024). However, Generation Y generally adopted a more cautious attitude, giving greater consideration to the benefits and security of new technologies before adoption (Agustin et al., 2025; Chan & Lee, 2023; Fintech Finance News, 2022). Although AI adoption has been widely studied, most research focuses on sectors other than banking, such as healthcare, higher education, and SMEs (Aldraiweesh & Alturki, 2025; Alka'awneh et al., 2025; Emon & Khan, 2025; Mustofa et al., 2025). Research examining Indonesia's banking sector remain limited (Ikhsan et al., 2025). Furthermore, few studies have jointly examined awareness, perceived ease of use, and security to explain AI adoption, particularly among Generation Y and Generation Z. This research offers novelty by comparing technology adoption behavior between Generations Y and Z within banking operations powered by artificial intelligence (AI). Most previous investigations examined technology adoption intentions without distinguishing between generations or focused on a single generational group (Byambaa et al., 2025; Menezes et al., 2025; Noreen et al., 2023; Rahman et al., 2021; Ramos et al., 2025). Differences in characteristics, technological experience, and level of technological understanding can influence the decision-making process for adopting AI. Li et al. (2025) argued that the Technology Acceptance Model (TAM) has limitations in explaining the complexity of modern technology use. Therefore, this research adopted an extended TAM by incorporating external variables to capture psychological and contextual factors beyond the original model.

TAM was considered more appropriate than the Unified Theory of Acceptance and Use of Technology (UTAUT) despite the limitations. Although both models are widely used to explain technology adoption, TAM has been extensively applied in AI adoption research within the banking sector and provides a focused framework for examining how individual perceptions influence attitudes and behavioral intentions (Ikhsan et al., 2025). TAM offered flexibility for incorporating context-specific external variables, allowing constructs such as awareness and perceived security to be integrated into the model. UTAUT includes determinants such as social influence and facilitating conditions that are

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beyond the scope of the present research. Recent evidence suggests that social influence does not significantly influence AI banking adoption (Papathomas et al., 2025). TAM provides a more focused and theoretically consistent framework for examining the effects of awareness, perceived ease of use, and perceived security on users' attitudes and intention to adopt AI-powered banking services. This research extends TAM by incorporating awareness and perceived security alongside perceived ease of use. The extended model is expected to provide a more comprehensive explanation of AI adoption and offer insights to help banks strengthen user trust and encourage adoption of AI-powered banking services.

2. Literature Review

2.1 Technology Acceptance Model (TAM) Theory

Technology Acceptance Model (TAM) is the most widely used framework for explaining AI adoption in banking. Its two core constructs, perceived usefulness (PU) and perceived ease of use (PEOU), influence users' attitudes (ATT) and the intention to adopt AI (ITT) (Naszariah et al., 2024; Purwianti et al., 2025). Developed from the Theory of Reasoned Action (TRA) theory, TAM explains technology adoption through the relationships among beliefs, attitudes, intentions, and behaviors (Rana et al, 2025). Information technology transactions in banking include concerns related to financial risk, data security, and trust, making external variables important for extending the TAM to explain user acceptance more effectively (Ikhsan et al., 2025; Naszariah et al., 2024).

In the Indonesian banking context, where AI adoption is still developing, understanding users' perceptions is essential. Factors such as awareness (AW), PEOU, and perceived security (PS) shape users' ATT and ITT toward AI-based banking services (Ikhsan et al., 2025). Therefore, this research adopted an extended TAM by incorporating AW and PS as key antecedents of ATT and ITT (Naszariah et al., 2024).

2.2 The Role of Awareness on Attitude

Awareness (AW) is an individual's understanding and learning of AI. This knowledge is needed for the appropriate use of AI, especially in technology services (Flavián et al., 2022). Previous research has shown that enhanced consciousness could lead to a positive view toward AI, while a lack of AW could lead to rejection of the ITT (Alzahrani, 2023; Rahiman & Kodikal, 2024).

H1: AW has a positive effect on ATT toward banking services

2.3 The Role of Awareness on Intention to Adopt AI

Noreen et al. (2023) confirmed that AW was strongly and favorably influenced by the ITT. Customers with a clear understanding of AI benefits, features, and usage methods showed a greater tendency to embrace AI services. This supports earlier research suggesting that understanding AI and the advantages is essential for its acceptance and use (Flavián et al., 2022; Lim et al., 2025; Menezes et al., 2025; Noreen et al., 2023; Roongta & Roongta, 2024; Sharma & Singh, 2024; S. Singh & Kumar, 2025).

H2: AW has a positive effect on ITT in banking services

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2.4 The Role of Perceived Ease of Use on Attitude

PEOU is the extent to which an individual believes using technology will be easy (Ikhsan et al., 2025; Jisham et al., 2025). Technology with a straightforward operating system and a user-friendly interface will foster a more positive outlook (Geddam et al., 2024). PEOU provides a comfortable, minimally obstructive user experience, thereby strengthening users' belief in the benefits of the technology (Hossain & Biswas, 2024; Ikhsan et al., 2025). However, a complex and time-consuming experience can lead to discomfort, confusion, and negative attitudes, hindering technology acceptance. In AI-driven banking services, factors such as ease of access, simple navigation, and flexibility of use play a key role in shaping positive user perceptions of the technology (Duarte & Baptista, 2025; Jisham et al., 2025; Singh & Kumar, 2025).

H3: PEOU has a positive effect on ATT toward banking services

2.5 The Role of Perceived Ease of Use on Intention to Adopt AI

TAM theory views PEOU as a key factor influencing adoption intention, helping reduce cognitive barriers and boost user readiness to adopt new technologies. Greater ease of use and lower effort requirements increased user willingness to adopt the technology (Hasan et al., 2023; Prastiawan et al., 2021; Ramos et al., 2025; Sharma & Singh, 2024). In AI-powered banking services, straightforward access and usability motivate users' acceptance (Padi et al., 2026; Samuel et al., 2026).

H4: PEOU has a positive effect on ITT in banking services

2.6 The Role of Perceived Security on Attitude

PS is defined as users' impressions of how secure a digital system or service is, including risks such as transaction security. A strong security setup can boost users' confidence and foster positive perceptions of digital services. In particular, in the case of mobile banking, security features such as transaction encryption and two-factor authentication have been shown to foster favorable user ATT toward these apps (Almaiah et al., 2023). A sense of security also enhances user convenience and trust, which promotes the acceptance of digital services, such as mobile wallets (Aprilia & Amalia, 2022). Therefore, a strong sense of PS tends to enhance positive user ATT toward AI-driven services (Alka'awneh et al., 2025; Aprilia & Amalia, 2022).

H5: PS has a positive effect on ATT toward banking services

2.7 The Role of Perceived Security on Intention to Adopt AI

PS is an important driver of customers' desire to use AI-based technology, especially in the banking sector. The perception that a system is capable of maintaining transaction security, protecting personal data, and preventing misuse of information can increase user trust and comfort, thereby driving user intentions (Sharma & Singh, 2024). However, a low level of perceived security, including risks to personal data and potential security breaches through information misuse, reduced user intention to adopt the technology. Research has shown that greater perceived system reliability increased the tendency to use digital services. Consequently, stronger perceptions of security positively increased user intention to use digital services (Alka'awneh et al., 2025; Safari et al., 2022; Sharma & Singh, 2024).

H6: PS has a positive effect on ITT in banking services.

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2.8 The Role of Attitude on Intention to Adopt AI

ATT represents users' personal judgement of a technology, showing a positive or negative ITT (Geddam et al., 2024; Jiao & Cao, 2024; Purwianti, Ariyanto, et al., 2025; Wahpiyudin et al., 2025). A positive ATT toward technology increases user confidence and promotes ITT (Ikhsan et al., 2025). In AI-enabled financial services, customers who view the technology's features and benefits positively tend to feel at ease and express higher intentions to adopt during banking activities (Noreen et al., 2023). Emotional experiences also influence ATT, the institution's reputation, and the quality of interactions with the technology. Previous research confirms that ATT strongly impacts ITT (Duarte & Baptista, 2025; Lopes et al., 2025; Roy et al., 2022; Suryadi et al., 2025).

H7: ATT has a positive effect on ITT in banking services

2.9 The Role of Awareness on Intention to Adopt AI, Mediated by Attitude

In the TAM theoretical framework, ATT mediates between user perceptions and intentions (Byambaa et al., 2025). Individual awareness contributed to the development of a positive attitude toward AI-based technologies (Rahiman & Kodikal, 2024). Greater understanding of AI increased the tendency to hold positive opinions about AI usage (Rahiman & Kodikal, 2024; Singh & Sinha, 2020). According to previous research, this positive outlook increases users' ITT (Ikhsan et al., 2025; Rahman et al., 2021). Users with a positive perception of technology are usually aware of service benefits, feel comfortable using AI, and have the desire to implement it in banking (Gálvez-Sánchez et al., 2026; Noreen et al., 2023). Therefore, AW shapes perceptions, which then influence ITT.

H8: AW has positive effect on ITT in banking services, with ATT as the mediating variable

2.10 The Role of Perceived Ease of Use on Intention to Adopt AI, Mediated by Attitude

In AI-driven banking services, simple access, intuitive navigation, and flexible use have been proven to enhance customers' positive perceptions of the technology (Duarte & Baptista, 2025; Jisham et al., 2025; S. Singh & Kumar, 2025). A positive ATT increases user confidence and promotes the implementation of technology (Ikhsan et al., 2025; Rahman et al., 2021). This variable enables users to perceive the service's superiority and convenience, thereby increasing the tendency to adopt technology in bank operations. (Byambaa et al., 2025; Lim et al., 2025). Greater perceived ease of use increased positive ATT toward AI, strengthening user motivation to use the technology.

H9: PEOU has positive effect on ITT in banking services, with ATT as the mediating variable

2.11 The Role of Perceived Security on Intention to Adopt AI, Mediated by Attitude

A solid security framework can boost user confidence and foster favorable perceptions of AI-based services (Almaiah et al., 2023; Salah & Ayyash, 2025). This positive ATT subsequently boosts individuals' urge to use and implement the technology (Ikhsan et al., 2025; Rahman et al., 2021).

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Individuals with positive ATT will be aware of technology's features and benefits, thereby showing higher ITT. Therefore, PS shapes ATT, which then influences ITT, as reported by previous research (Byambaa et al., 2025; Lim et al., 2025; Noreen et al., 2023).

H10: PS has a positive effect on ITT in banking services, with ATT as the mediating variable

3. Conceptual Framework

The adoption of AI-powered banking services is influenced by users' perceptions and evaluations of the technology. Based on TAM, this research proposed that AW, PEOU, and PS influenced users' ATT and ITT. Previous research suggests that AW enhances ATT, PEOU promotes favorable evaluations, and PS strengthens trust in AI-based services (Almaiah et al., 2023; Flavián et al., 2022; Hasan et al., 2023; Noreen et al., 2023; Sharma & Singh, 2024). Consistent with TAM, ATT is expected to mediate the relationship between these factors and ITT (Byambaa et al., 2025; Ikhsan et al., 2025). Based on these arguments, the conceptual framework and hypotheses of this research are proposed as follows (Figure 1).

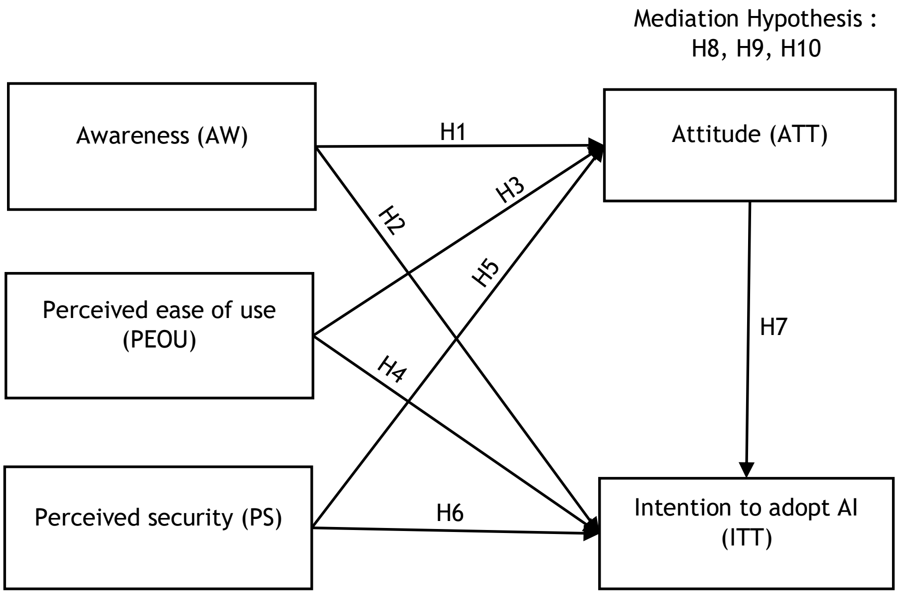

Figure 1. The conceptual framework for intention to adopt AI in banking services is influenced by attitude, awareness, perceived security, and ease of use.

The research hypotheses are outlined as follows:
H1: AW has a positive effect on ATT toward banking services.
H2: AW has a positive effect on ITT in banking services.
H3: PEOU has a positive effect on ATT in banking services.
H4: PEOU has a positive effect on ITT in banking services.
H5: PS has a positive effect on ATT toward banking services.
H6: PS has a positive effect on ITT in banking services.
H7: ATT has a positive effect on ITT in banking services.
H8: AW has positive effect on ITT in banking services, with ATT as the mediating variable.
H9: PEOU has positive effect on ITT in banking services, with ATT as the mediating variable.
H10: PS has positive effect on ITT in banking services, with ATT as the mediating variable.

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4. Methods

4.1 Research Design

A quantitative, comparative, and causal research design was adopted to investigate the relationships among AW, PEOU, and PS, as well as the effects on ITT, with ATT as a mediator. In particular, it focused on Indonesian bank customers who encountered or used AI-powered banking services. This methodology allowed the analysts to determine the causal relationship between the factors.

4.2 Sampling

A non-probability purposive sampling method was used to select Indonesian banking customers of BCA, BRI, BNI, Mandiri, and OCBC who had previous experience using AI banking services. The research specifically targeted Generation Z (17-28) and Y (29-44) because both groups were considered to have a greater tendency to adopt new technology. To ensure that respondents met the required criteria, screening questions were included at the beginning of the online questionnaire regarding respondents' age category, banking experience, and previous use of AI banking services. Responses that did not meet these criteria were excluded from the analysis.

The required sample size was estimated using GPower to ensure adequate statistical power before data analysis. GPower was used in previous research to determine the minimum sample size by considering the specified effect size, significance level, and desired statistical power (Konagalla et al., 2026). In the context of SEM analysis, previous research also used GPower to set parameters, such as medium effect size, statistical power, and significance level (Arantes et al., 2025). Therefore, this research applied a medium effect size of 0.15, a significance level (α) of 0.05, statistical power of 0.95, and the maximum number of predictors directed toward an endogenous construct in the model. The GPower results showed that the minimum required sample size was 226 respondents. In total, 418 valid responses were obtained and used for data analysis, which exceeded the minimum sample size recommended by GPower.

4.3 Measurement

Table 1 shows that the data were gathered using a standardized questionnaire. All constructs were analyzed with a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). All relevant indicators were taken from previous research to measure each variable, with detailed operational definitions provided in Table 1.

Table 1. Operational definitions of the relevant variables and indicators influencing intention to adopt AI in banking services

Variables	Operational Definition	Indicators	Sources
Awareness (AW)	Awareness of how AI-based technology tools can support ongoing routine activities	1) AW1. I am familiar with AI-driven services in banking.	(Rahiman & Kodikal, 2024)

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Table 1. Operational definitions of the relevant variables and indicators influencing intention to adopt AI in banking services (Continue)

Variables	Operational Definition	Indicators	Sources
Awareness (AW)	Awareness of how AI-based technology tools can support ongoing routine activities	2) AW2. I am aware that AI-based technology is useful for providing banking services. 3) AW3. AI technology efficiently offers information and responds to banking queries. 4) AW4. I know about applying AI in financial processes.	(Rahiman & Kodikal, 2024)
Perceived Ease of Use (PEOU)	The degree to which someone perceives a technology as easy and effortless to use.	1) PEOU1. I think it is quite easy to understand how to use AI-enabled banking technologies. 2) PEOU2. Handling banking transactions with AI-powered technology makes everything so simple for me. 3) PEOU3. I am confident that I can learn AI-based banking services quickly. 4) PEOU4. Interacting with AI in banking is simple for me because it requires little mental effort.	(Rahman et al., 2021)
Perceived Security (PS)	User evaluation of the level of protection and security provided when operating artificial intelligence technology	1) PS1. I feel confident sending sensitive data via AI-driven banking services. 2) PS2. AI-driven banking services offer a secure way to transmit sensitive data. 3) PS3. I feel completely secure sharing sensitive information through AI-enabled financial services. 4) PS4. In general, AI-enabled financial services are a safe option for sending sensitive data.	(Safari et al., 2022)

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Table 1. Operational definitions of the relevant variables and indicators influencing intention to adopt AI in banking services (Continue)

Variables	Operational Definition	Indicators	Sources
Attitude (ATT)	An individual's assessment of the use of AI-enabled services	1) ATT1. I believe that AI implementation in banking is beneficial. 2) ATT2. I believe AI technology enhances the efficiency of banking processes. 3) ATT3. I hold a positive view of AI's role in banking. 4) ATT4. I support utilizing AI technology within the banking sector. 5) ATT5. I believe that AI technology enhances my overall banking experience.	(Fang et al., 2025; Singh and Kumar, 2025)
Intention to Adopt AI (ITT)	Individuals want to adopt and utilize AI-based technologies.	1) ITT1. I am going to use AI technology in financial services. 2) ITT2. I am going to operate banking services using AI-powered banking technologies. 3) ITT3. I plan to rely on AI-powered banking services instead of consulting a human financial advisor. 4) ITT4. I might suggest to my family and friends that they try using AI technology for banking.	(Lim et al., 2025; Ramos et al., 2025)

4.4 Data collection

Data and respondent responses were collected using an online Google Forms questionnaire and distributed across platforms, such as Instagram, Telegram, WhatsApp, and personal networks. Respondents who met the research criteria completed the survey independently within a specified period, without direct contact with the analysts. Secondary data from academic journals, previous research, and reports from trustworthy institutions were also used to strengthen the research framework.

4.5 Data Analysis

Data were analyzed using Smart-PLS 4, and descriptive statistics were used to summarize respondents' demographic characteristics, as well as provide an overview of the research variables. Because the data were collected through a self-administered online questionnaire, Common Method Bias (CMB) was assessed using Harman's single-factor test. The first factor explained 34.75% of the total variance, which was below the recommended threshold of 50%. Therefore, CMB was not considered a significant concern in this study.

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The measurement model was then assessed for validity and reliability. Convergent validity was evaluated using indicator loadings and Average Variance Extracted (AVE). Meanwhile, discriminant validity was assessed using the Fornell-Lacker criterion. Reliability was examined using Cronbach's alpha (CA) and Composite Reliability (CR).

The structural model was evaluated by examining the coefficient of determination (R^2) and effect sizes (f^2). Hypothesis testing was conducted using the bootstrapping procedure in SmartPLS 4, with significance determined based on t-values and p-values. PLSpredict and CVPAT analyses were carried out to assess predictive performance. Furthermore, measurement invariance between Generations Y and Z was established using the Measurement Invariance of Composite Models (MICOM) procedure before conducting MGA analysis to identify significant differences in structural relationships.

5. Findings

5.1 Respondent Characteristics

This section presents the demographic characteristics of the research's respondents. A total of 418 valid responses were included in the analysis. Female respondents accounted for the majority of the sample (324; 78%), while the distribution between Generations Z (207; 50%) and Y (211; 50%) was relatively balanced. Most respondents had attained higher education (209; 50%), followed by high school or vocational education (191; 46%). Students represented the largest occupational group (193; 46%), followed by private sector employees (132; 32%). More than half of the respondents reported a monthly income below IDR 4,999,999 (231; 55%). Among the banking institutions used, Bank BCA was the most frequently selected (233; 38%), followed by Bank BRI (162; 26%). In general, the respondents were predominantly educated young adults with experience using banking services.

5.2 Reliability and Validity Test

Analysis of 418 respondents showed that the fifth indicator in the ATT construct and the fourth indicator in the PEOU construct had outer loadings below 0.60, leading to removal from the model. Table 2 shows that after eliminating these indicators, all remaining indicators exceeded the acceptable threshold. Although several indicators retained loadings between 0.60 and 0.70, these items were retained because previous research in PLS-SEM suggests that indicators within this range may still be considered acceptable, particularly when the constructs demonstrate adequate convergent validity and CR (Hair et al., 2019). Additional indicators with loadings slightly below 0.70 were omitted to preserve the content validity of the constructs (Hair et al., 2021). Furthermore, all constructs achieved satisfactory AVE, CA, and CR values, suggesting that the measurement model met the recommended standards for validity and reliability. Internal consistency reliability was assessed using CA ($\geqslant 0.70$) and CR ($\geqslant 0.60$) (Hair & Alamer, 2022).

The coefficient of determination (R^2) was used to assess the explanatory power of the structural model for both Generations Z and Y. The results showed that the model explained 46.3% and 38.8% of the variance in ATT, respectively. Furthermore, the model explained 70.4% and 67.2% of the variance in ITT for Generation Z and Y, respectively. According to Hair et al. (2021), these results showed that the structural model moderated explanatory power across both groups.

Table 2. Reliability and validity results

Variables	Generation Y					Generation Z				
	Outer Loading	AVE	CA	CR	R^2	Outer Loading	AVE	CA	CR	R^2
Attitude										
ATT1	0.747					0.729				
ATT2	0.765	0.564	0.738	0.837	0.368	0.754	0.546	9.720	0.827	0.463
ATT3	0.660					0.652				
ATT4	0.822					0.813				
Awareness										
AW1	0.839					0.834				
AW2	0.796	0.648	0.819	0.880		0.860	0.699	0.857	0.903	
AW3	0.777					0.833				
AW4	0.806					0.818				
Intention to adopt AI										
ITT1	0.812	0.557	0.735	0.833	0.672	0.756	0.575	0.755	0.844	0.704
ITT2	0.761					0.770				
ITT3	0.653					0.770				
ITT4	0.750					0.737				
Perceived Ease of Use										
PEOU1	0.826	0.586	0.646	0.809		0.725	0.566	0.808	0.796	
PEOU2	0.728					0.748				
PEOU3	0.739					0.782				
Perceived Security										
PS1	0.824	0.588	0.765	0.850		0.816	0.633	0.618	0.873	
PS2	0.762					0.787				
PS3	0.773					0.798				
PS4	0.704					0.780				

Discriminant validity was assessed to confirm that the model's variables were conceptually distinct from one another. All constructs in the framework achieved independent empirical identification (Hair et al., 2021). The Fornell-Lacker criteria were used to compare the AVE of each construct with the inter-construct correlations. All constructs met these requirements, confirming the model's discriminant validity (Table 3).

Table 3. Fornell-Lacker criterion (Generations Z and Y)

Variables	**ATT**	**AW**	**ITT**	**PS**	**PEOU**
Generation Z					
ATT	0.739				
AW	0.545	0.836			
ITT	0.629	0.709	0.759		
PS	0.526	0.262	0.383	0.795	
PEOU	0.424	0.458	0.682	0.358	0.752
Generation Y					
ATT	0.751				
AW	0.532	0.805			
ITT	0.666	0.697	0.746		
PS	0.371	0.225	0.405	0.767	
PEOU	0.469	0.497	0.610	0.252	0.766

Note: AW = Awareness; PEOU = Perceived ease of use; PS = Perceived security; ATT = Attitude; ITT = Intention to adopt AI

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5.3 Structural Model Assessment (f^2 effect size, PLSpredict and CVPAT)

5.3.1 Effect Size (f^2)

The effect size (f^2) assessment was carried out to evaluate the contributions of each exogenous construct to the endogenous constructs across both Generations. Following the guideline that f^2 values of 0.02, 0.15, and 0.35 represented small, medium, and large effects, respectively, the results show that the magnitude of predictor contributions varied across both generational groups (Guenther et al., 2023). In Generation Z, AW had a medium effect on ATT (f^2 = 0.227) and ITT (f^2 = 0.332), while PS had a medium effect on ATT (f^2 = 0.238). PEOU showed a large effect on ITT (f^2 = 0.381), but had no meaningful effect on ATT (f^2 = 0.015). Furthermore, PS did not affect ITT (f^2 = 0.000), suggesting that its contribution was more relevant to shaping ATT than to directly influencing ITT among Generation Z.

In Generation Y, AW showed a medium effect on ATT (f^2 = 0.162) and ITT (f^2 = 0.294). ATT also demonstrated a medium effect on ITT (f^2 = 0.158). Meanwhile, PS had a small effect on both ATT (f^2 = 0.080) and ITT (f^2 = 0.058), while PEOU showed small effects on ATT (f^2 = 0.063) and ITT (f^2 = 0.124). In general, these results showed that AW consistently contributed to ATT formation and ITT across both generations. The influence of PEOU and PS differed between Generations Z and Y.

5.3.2 Predictive Relevance Assessment

PLSpredict analysis was carried out to assess the out-of-sample predictive capability of the proposed model. Following the guidelines of Shmueli et al. (2019) and Guenther et al. (2023), predictive relevance was evaluated by comparing the PLS-SEM model's prediction errors with those of the Linear Model (LM) benchmark using RMSE values. A model was considered to have stronger predictive capability when the PLS-SEM prediction error was lower than the LM benchmark for most or all indicators.

The results showed that Table 4 the PLS-SEM model had lower RMSE values than the LM benchmark for only two indicators, namely ATT4 and ATT5. However, the LM benchmark performed better for the remaining indicators, including ATT1, ATT2, ATT3, ITT1, ITT2, ITT3, and ITT4. Although the proposed model showed predictive relevance for a limited number of indicators, its out-of-sample predictive capability remained weak, as most indicators had lower prediction errors under the LM benchmark. Therefore, the model's predictive performance should be interpreted with caution, particularly when making generalizations beyond the analyzed sample.

Table 4. Cross-validated predictive ability test (CVPAT) results

Benchmark Comparison	Construct	PLS Loss	Benchmark Loss	Average Loss Difference	T-value	P-value	Result
PLS-SEM vs Indicator Average (IA)	ATT	0.456	0.578	-0.122	4.859	0.000	PLS-SEM performs better
PLS-SEM vs Indicator Average (IA)	ITT	0.511	0.819	-0.308	7.811	0.000	PLS-SEM performs better

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Table 4. Cross-validated predictive ability test (CVPAT) results (Continue)

Benchmark Comparison	Construct	PLS Loss	Benchmark Loss	Average Loss Difference	T-value	P-value	Result
PLS-SEM vs Indicator Average (IA)	Overall	0.480	0.685	-0.205	7.455	0.000	PLS-SEM performs better
PLS-SEM vs Linear Model (LM)	ATT	0.456	0.434	0.022	2.333	0.000	LM performs better
PLS-SEM vs Linear Model (LM)	ITT	0.511	0.363	0.148	8.886	0.000	LM performs better
PLS-SEM vs Linear Model (LM)	Overall	0.480	0.402	0.078	8.466	0.000	LM performs better

Cross-validated Predictive Ability Test (CVPAT) was conducted as an additional predictive assessment to evaluate the proposed PLS-SEM model's predictive capability. According to Guenther et al. (2023), the CVPAT enabled the analysts to statistically compare the predictive performance of a PLS-SEM model with benchmark models, including Indicator Average (IA) and the more demanding LM. The CVPAT results showed that the PLS-SEM model achieved lower prediction loss than the IA benchmark for ATT, ITT, and the general model. This result suggested that the proposed model outperformed the naïve benchmark. However, compared with the LM benchmark, the PLS-SEM model showed higher prediction losses. These differences were statistically significant, as evidenced by p-values below 0.05. Although the proposed model showed predictive capability relative to the IA benchmark, its performance was lower than that of the more demanding LM benchmark.

5.4 Measurement Invariance of Composite Models (MICOM) Procedure

According to Rungruangjit and Charoenpornpanichkul (2024), before conducting Multi-Group Analysis (MGA) in PLS-SEM research, MICOM procedure was recommended to ensure that the constructs were measured equivalently across groups. MICOM helped verify that the measurement models captured the same attributes across different conditions, thereby safeguarding the validity of group-comparison results. In the research, permutation-based measurement invariance testing was conducted for respondents before performing MGA. The MICOM procedure consisted of three sequential steps for assessing measurement invariance. Step 1 assessed configural invariance by ensuring that the same indicators, data treatment procedures, and algorithm settings were applied across groups. Step 2 evaluated compositional invariance by examining whether the original correlation exceeded the 5th percentile and whether the permutation *p* value exceeded 0.05. Step 3 assessed the equality of group means and variances. Full measurement invariance was established when both the mean and variance differences fell within the 2.5% and 97.5% confidence interval boundaries. However, partial measurement invariance was considered sufficient to proceed with MGA analysis in PLS-SEM research. Table 5 shows the detailed MICOM results of this research.

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Table 5. Measurement invariance of composite models (MICOM) results

Constructs	Confi. Inv. (Step 1)	Original Corr.	5.0%	Partial Measurement Inv.	Original mean diff.	Confidence Interval (2.5%; 97.5%)	Original Variance Diff.	Confidence Interval (2.5%; 97.5%)	Full Measurement inv.
ATT	Yes	0.999	0.994	Yes	-0.030	[-0.201;0.187]	-0.031	[-0.464;0.446]	Yes/ Yes
AW	Yes	0.999	0.998	Yes	0.019	[-0.202;0.187]	-0.232	[-0.302;0.318]	Yes/ Yes
ITT	Yes	0.995	0.997	No	-0.016	[-0.194;0.195]	-0.027	[-0.359;0.392]	No/ Yes
PS	Yes	0.998	0.991	Yes	0.017	[-0.188;0.200]	-0.190	[-0.372;0.333]	Yes/ Yes
PEOU	Yes	0.992	0.990	Yes	-0.040	[-0.194;0.192]	0.091	[-0.349;0.354]	Yes/ Yes

Note: AW = Awareness; PEOU = Perceived ease of use; PS = Perceived security; ATT = Attitude; ITT = Intention to adopt AI

The MICOM analysis showed that configural invariance was established across both groups. In Step 2, compositional invariance was achieved for most constructs, as the original correlation values exceeded the 5% quantile values and the permutation p-values were above 0.05. In Step 3, all constructs satisfied the equality-of-means-and-variance assessment criteria because the original differences fell within the confidence interval boundaries. In general, the MICOM result showed that the measurement model was sufficiently invariant to proceed with MGA.

5.4 Multi-Group Analysis (MGA)

Table 6 show that MGA Analysis was used to explore possible generational differences and the relationships among AW, PEOU, PS, ATT, and ITT. This method provided insights into the impact of generational factors on the connections. Bootstrapped path coefficient testing in the MGA identified both similarities and differences between the groups regarding AI-driven banking service adoption. Both groups agreed that AW positively influenced ATT and ITT ($p < 0.05$). Furthermore, ATT significantly influenced intentions in both groups. Differences included Millennials valuing PS and PEOU, which positively influenced ITT ($p < 0.05$). Generation Z did not see PS as significantly affecting ITT ($p > 0.05$), and PEOU did not positively influence ATT ($p > 0.05$). However, both factors were relevant elsewhere. The results showed that Millennials focused on PS and PEOU, while Generation Z considered other factors when accepting AI technology. This showed differences in how ATT mediated the relationship between ITT and AW among Millennials and Generation Z. For both groups, AW influences ATT, which in turn affects ITT ($p < 0.05$). In Millennials, PEOU impacts ATT ($p < 0.05$), but not for Generation Z ($p > 0.05$). PS influenced Generation Z's ITT through ATT ($p < 0.05$), a mediation not observed among Millennials. These results suggested that the mediating mechanisms underlying ITT differ across generations. The Millennials showed stronger influence from AW and PEOU, increasing ITT, while Generation Z showed stronger influence from AW and PS through ATT before forming ITT.

Table 6. Multi-Group Analysis (MGA) hypothesis testing between Generations Y and Z

Hypothesis	Generation Z				Generation Y (Millennials)			
	Path Coef.	T-value	p-values	Results	Path Coef.	T-value	p-values	Results
ATT → ITT	0.235	3.213	0.001	Supported	0.278	3.576	0.000	Supported
AW → ATT	0.384	6.010	0.000	Supported	0.332	4.727	0.000	Supported
AW → ITT	0.398	6.090	0.000	Supported	0.392	4.703	0.000	Supported

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Table 6. Multi-Group Analysis (MGA) hypothesis testing between Generations Y and Z (Continue)

Hypothesis	Generation Z				Generation Y (Millennials)			
	Path Coef.	T-value	p-values	Results	Path Coef.	T-value	p-values	Results
PS → ATT	0.381	6.089	0.000	Supported	0.218	2.661	0.008	Supported
PS → ITT	0.026	0.680	0.497	NS	0.149	2.811	0.005	Supported
PEOU → ATT	0.127	1.509	0.131	NS	0.291	3.684	0.000	Supported
PEOU → ITT	0.366	5.364	0.000	Supported	0.238	3.362	0.001	Supported
AW → ATT→ITT	0.090	2.887	0.004	Supported	0.092	2.642	0.008	Supported
PS → ATT → ITT	0.090	2.718	0.007	Supported	0.061	1.783	0.075	NS
PEOU →ATT →ITT	0.030	1.327	0.184	NS	0.081	3.039	0.002	Supported

Note: AW = Awareness; PEOU = Perceived ease of use; PS = Perceived security (PS); ATT = Attitude; ITT = Intention to adopt AI; NS = Not Supported

6. Discussion

6.1 Direct effects

6.1.1 The Relationship between Awareness and Attitude

AW greatly influenced ATT, supporting hypothesis H1, and confirming the important role of awareness in shaping positive attitudes. This result was consistent with previous research suggesting that greater knowledge and understanding of AI technology could reduce uncertainty, boost acceptance, and promote a positive outlook on its use in banking services (Alzahrani, 2023; Flavián et al., 2022; Rahiman & Kodikal, 2024). Individuals familiar with AI's role in banking generally viewed the technology positively because AI functioned as a helpful tool for banking tasks, improved processing speed, and delivered information efficiently (Ikhsan et al., 2025). This knowledge directly supported the idea that the use of AI in banking was good, important, and worth pursuing. The MGA results also showed that AI's influence was consistent across the two groups. This suggests that comprehending AI technology was a significant reason why different generations respond differently.

6.1.2 The Relationship between Awareness and Intention to Adopt AI

H2 is supported by the effect of AW on ITT, confirming that greater awareness increased information technology transactions. Greater familiarity with AI increased the tendency to develop positive perceptions of AI benefits, features, and usability, thereby improving adoption (Menezes et al., 2025; Sharma & Singh, 2024). In addition, a higher tendency to use AI in banking contexts was connected with better awareness of the basic principles, operational procedures, and prospective advantages, which was associated with a stronger inclination for implementation (Sharma & Singh, 2024). Users' perception of AI was often associated with increased confidence in the use of technology for financial services (Menezes et al., 2025).

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According to previous research, familiarity tended to be associated with increased ease and comfort in using (Lim et al., 2025). The effect was observed across both groups, with Generation Z, generally more technologically proficient, showing an earlier tendency to adopt AI for banking. Similarly, awareness of AI benefits and applications increased confidence among Generation Y and strengthened AI adoption in banking activities.

6.1.3 The Relationship between Perceived Ease of Use and Attitude

PEOU significantly influences ATT, supporting H3 and confirming that greater ease of use strengthened positive attitudes toward AI. According to previous research, customers were more inclined to have a favorable perception of technology when technology required less effort and offered greater ease of use (Alzboon et al., 2025; Byambaa et al., 2025; Foroughi et al., 2024; Geddam et al., 2024; Hossain & Biswas, 2024; Huang & Huang, 2025). In a situation where AI in banking was easy to understand and use, lower mental effort increased positive ATT toward the technology. Therefore, the technology was considered practical and useful because it provided a convenient and efficient experience (Foroughi et al., 2024). MGA results show that PEOU did not significantly affect Generation Z's perception of AI. This generation is digital natives with stronger technological literacy and regarded ease of use as a core feature rather than an additional benefit, influencing technology appraisal (Hossain & Biswas, 2024). Meanwhile, Generation Y appreciated the simplicity of use, especially for its convenience, leading to a good image of AI in banking. PEOU also had a big effect on users who were not experienced with digital technology (Alzboon et al., 2025). This showed that the effect of PEOU depended on the familiarity of individuals with digital tools by generation.

6.1.4 The Relationship between Perceived Ease of Use and Intention to Adopt AI

The results of H4 showed that PEOU of AI significantly influenced ITT. Greater PEOU increased user satisfaction, reduced mental effort, and strengthened confidence in the benefits of technology, as shown in previous research (Hasan et al., 2023; Prastiawan et al., 2021; Rahman et al., 2021; Ramos et al., 2025). Simplifying technology use reduced the perceived barriers to implementation (Rahman et al., 2021). The basic format appeared reliable and easy to use for everyday banking, increasing adoption and user support (Safari et al., 2022). The effects were observed across Generations Z and Y, showing the importance of usability in technology adoption across both groups. Individuals of different ages used technology differently, yet ease of use remained crucial in banking services.

6.1.5 The Relationship between Perceived Security and Attitude

PS impacts ATT strongly, supporting H5 and confirming the important role of perceived security in shaping positive attitudes toward AI. Previous research showed that strong digital security safeguarding data protection, privacy, and transaction authentication increased user trust and comfort, leading to a more positive perception of the technology (Alka'awneh et al., 2025; Almaiah et al., 2023; Aprilia & Amalia, 2022). A positive opinion of technology was often related to confidence in AI-powered banking services, which promoted adoption (Almaiah et al., 2023). More security could help allay fears of data abuse and add more confidence in digital organizations.

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Based on the MGA results, PS did not influence the perspective of Generation Z. This result suggested that safety perception had no substantial impact on the perception of AI technology, as stated by Alka'awneh et al (2025). However, security concerns continued to shape user perceptions and influenced attitudes toward technology adoption. In any case, the impact depended on the environment and varied among generations in terms of trust and experience with digital technologies.

6.1.6 The Relationship between Perceived Security and Intention to Adopt AI

The result supports H6 because PS significantly influence ITT, confirming the important role of perceived security. This was consistent with previous research showing that data privacy and transaction safety enhanced users' trust and confidence, thereby supporting ITT. Trust in technology was also associated with the adoption of digital systems. Perceived system security increased the tendency to adopt and support digital systems (Alka'awneh et al., 2025; Safari et al., 2022; Sharma & Singh, 2024). MGA results showed that PS had a minimal effect on AI adoption among Generation Z. However, Generation Z valued safety and believed in digital networks, which had little or no influence on decisions (Alka'awneh et al., 2025). PS strongly influenced technology choices among Generation Y because confidence in transaction and data security increased the tendency to use financial services. Therefore, the results showed that the importance of PS in ITT differed across generations.

6.1.7 The Relationship between Attitude and Intention to Adopt AI

The results supported H7 by showing that ATT significantly influenced ITT. This result correlated with the results of previous research that a positive ATT towards technology increased user confidence, comfort, and AW of the benefits of the service, thereby facilitating ITT (Duarte & Baptista, 2025; Lim et al., 2025; Lopes et al., 2025; Noreen et al., 2023). A positive perception of AI in banking as beneficial and efficient increased the tendency to use the technology. This cognitive and emotional ATT results in behavioral preparedness and an intention to use. The result supported the idea that ATT was vital for technological acceptability, mediating perceptions and actual use (Duarte & Baptista, 2025). Lim et al. (2025) also suggested that favorable user attitudes toward technology increased the tendency to use and support the service. The result showed that ATT influenced ITT across all age groups. Furthermore, positive views increased willingness, suggesting that ATT strengthened perceptions about ITT in banking.

6.2 Indirect effect

6.2.1 Attitude Mediates the Relationship between Awareness and Intention to Adopt AI

H8 confirmed that ATT mediated the relationship between AW and ITT. This result was consistent with a previous report that AW led to a favorable ATT, thereby influencing ITT (Rahiman & Kodikal, 2024). AI primarily influenced initial perceptions rather than directly shaping adoption readiness because understanding AI's role in banking fostered positive views of its usefulness and practicality, which subsequently increased adoption. This result was consistent with the TAM model, where ATT connected perceptions to ITT (Ikhsan et al., 2025). The development of favorable ATT required greater knowledge to promote positive ITT (Rahiman & Kodikal, 2024). According to the MGA analysis, the mediation effect was observed in both groups, suggesting that AW influenced ATT, which subsequently increased ITT across both generations. Individuals followed similar patterns, although some variations were observed, as AW of technology shaped ATT, which subsequently increased ITT in the banking sector.

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6.2.2 Attitude Mediates the Relationship between Perceived Ease of Use and Intention to Adopt AI

ATT was a key driver of the effect of PEOU on ITT, thereby validating H9. This is consistent with other research indicating that PEOU improves ATT toward technology and then ITT (Jisham et al., 2025; Rahman et al., 2021). PEOU offers immediate benefits and fosters positive views of the technology. When users perceived AI as simple to use, positive ATT increased, thereby strengthening intention to adopt the technology (Rahman et al., 2021). MGA analysis indicates that the mediation effect is significant only for Generation Y. PEOU alone does not shape ATT leading to ITT in Generation Z. Because of familiarity with digital technology, PEOU alone was insufficient to develop strong ATT (Byambaa et al., 2025). Although the technology is straightforward to operate, it has little effect on ATT, resulting in an insignificant mediation effect. For Generation Y, PEOU affects ATT and ITT, depending on their digital familiarity.

6.2.3 Attitude Mediates the Relationship between Perceived Security and Intention to Adopt AI

Confirming H10, ATT serves as a mediator between PS and the ITT. Consistent with previous research, PS produced a good ATT that enhanced the ITT (Almaiah et al., 2023; Byambaa et al., 2025; Ikhsan et al., 2025). Results of MGA showed relevance for Generation Z in this mediation. PS was in the eye of the beholder, creating safety and increasing impressions of technology. The perception that AI banking protected information and transactions was a major factor in the positive ratings it receives and the tendency to use AI services. Almaiah et al. (2023) observed that users felt PS could boost ITT by shaping ATT as an evaluative response to technology. The MGA results showed a significant mediation effect for Generation Z, suggesting that PS influenced adoption through the development of positive ATT. Generation Z tend to look at experiences and perceptions (Byambaa et al., 2025). Furthermore, Generation Z did not automatically perceive the technology as safe, leading to uncertainty toward its use. Therefore, the impression of technology security throughout the generations could be absorbed and processed differently, resulting in a variable mediator between PS and ATT.

6.3 Managerial Implications

This research had practical implications for the Indonesian banking industry, particularly for the development and effective implementation of AI-based services. Banks could use these insights to educate clients about AI technology through focused education campaigns, digital marketing, and by clearly explaining the functions and benefits of AI services. A good communication strategy will drive more consumers to accept AI, as AW is a huge factor in ITT. Banks also need to adapt efforts to different age groups. For example, Generation Y needs a simple, reliable interface with high data protection. Meanwhile, Generation Z placed greater value on user experience and innovative features because of stronger receptiveness to new technologies. Improving service quality, user experience, and interactive responsiveness therefore remained essential for strengthening public attitudes toward AI. This is extremely essential considering the strong influence of sentiment on AI adoption across both generations.

6.4 Theoretical Implications

This research aimed to enhance the classic TAM model by including AW and PS to observe the impact of these factors on ITT. The results showed that AW reliably changed user ATT and ITT, suggesting the importance of first cognitive assessments of adoption. Furthermore, ATT was an important mediator that connected perceptions to ITT.

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The MGA results also showed generational disparities in the technology adoption processes. In summary, adoption of technology differed among demographic groups, especially generations.

6.5 Limitations

This study has several limitations that should be acknowledged. First, this research only included bank consumers in Indonesia, which would limit the generalizability of the results to other nations because of cultural and technological differences. Second, the research examined only three variables, while factors such as social influence and perceived usefulness may also affect intention to adopt AI. Finally, as a cross-sectional research, it was not possible to assess changes in AI-related beliefs and behaviors over time.

7. Conclusions

In conclusion, this research analyses the impact of AW, PEOU, and PS on ITT in Indonesian banks, as well as the differences in ATT and age. The results show that all these variables positively affect ITT, both directly and indirectly through a mediator. Across all generations, AW is a common driver of ATT and ITT. ATT also serves as a key mediating factor in the implementation process. The MGA results show age-related differences, with the Millennials having stronger influence from PEOU and PS than Generation Z. Finally, the data show that both technological factors and generational traits influence the uptake of AI.

8. Recommendations

Based on the results and limitations, recommendations have been provided to guide future investigations and practitioners. Future research should investigate additional factors that may influence technology implementation to develop a more comprehensive understanding of the adoption process. Furthermore, longitudinal research can be useful for following the evolution of user behavior over time. Indonesian banks need to focus more on AI education and development, and on establishing new services that are easy, safe, and fun for all age groups. There is also a need to establish a more accurate and effective generational segmentation method for AI service development strategies.

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