

DO WE STILL NEED HUMAN IN DIGITAL BANKING? REDESIGN OF ARTIFICIALLY INTELLIGENT DEVICE USE ACCEPTANCE (AIDUA) MODEL MODERATED BY GENDER DIFFERENCES



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ABSTRACT

This study modifies and tests the Artificially Intelligent Device Use Acceptability (AIDUA) model in the Indonesian setting to assess consumer acceptability of Artificially Intelligent Devices (AIDs) in digital banking services. The study specifically examines how performance expectancy, hedonic incentive, social influence, and perceived intrusiveness influence users' desire to use AIDs. It also looks at how gender regulates this willingness. 96 legitimate respondents with prior experience with AI-based digital banking services provided data for the study, which used a quantitative explanatory research approach. Both measurement and structural models were evaluated through the use of Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0. The findings indicate that hedonic motivation, social influence, and perceived intrusiveness significantly affect willingness to use AIDs, while performance expectancy does not. Additionally, gender does not moderate the relationship between the cognitive constructs and behavioral intention. The model explains 94.8% of the variance in users' willingness, suggesting strong explanatory power. The results suggest that, from a practical perspective, financial institutions should place more emphasis on AI interfaces that are emotionally compelling, socially acceptable, and privacy-preserving than just performance advantages. This study contributes to our understanding of AI's adoption in banking and offers valuable insights for developing digital banking systems that are inclusive and trustworthy.

Keywords: Social Influence; Performance Expectancy; Perceived Intrusiveness; Hedonic Motivation; Willingness to use AI Device; Digital Banking

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INTRODUCTION

The banking industry is undergoing an unprecedented level of digital transformation thanks to technological advancements that put speed, convenience, and cost-effectiveness first (Alam et al., 2025). Artificially Intelligent Devices (AIDs), such as chatbots, robo-advisors, and intelligent virtual assistants, are among these advancements that have grown in importance in banking operations (Jung et al., 2021; Cimpanu et al., 2023). With no human involvement, these AI-powered platforms can now handle a variety of functions, including financial planning and customer support (Kasula, 2023). The question of whether human presence is still necessary for digital financial services remains, nonetheless, despite the advancements in technology and the extensive use of AIDs.

Incorporating AIDs into digital banking presents behavioral and psychological issues in addition to a technological change (Ologun et al., 2025). A number of elements, including trust, perceived value, perceived intrusiveness, and emotional connection, influence consumers' acceptance of AIDs in addition to system performance. By examining how cognitive assessments impact feelings, attitudes, and eventually behavioral intentions toward AI systems, the Artificially Intelligent Device Use Acceptance (AIDUA) model offers a strong framework for comprehending these dynamics (Gursoy et al., 2019). However, this approach needs to be reaffirmed and contextualized, particularly in developing nations where banking culture, cultural expectations, and digital literacy are different from those in more industrialized economies.

Researchers' opinions on how customers react to Artificially Intelligent Devices (AIDs) have diverged as a result of the increasing use of AIDs in digital banking (Pedrosa, 2025). AID use has been linked to favorable emotional effects, according to a number of studies. For example, Gursoy et al. (2019) and Lu et al. (2020) discovered that when users engage with AI-powered banking tools, they frequently feel happy, satisfied, and empowered, especially when these systems are made to be responsive, effective, and contextually adaptive. These studies demonstrate how speed, customization, and convenience, features that are very compatible with the demands of tech-savvy generations, can improve the user experience with AIDs.

A rising corpus of research, on the other hand, offers a different viewpoint, suggesting that while interacting with AIDs, patrons may experience feelings of intimidation, anxiety, or emotional detachment (Pitardi & Marriott, 2021; Belanche et al., 2022). Concerns about data privacy, a lack of empathy, and the apparent complexity or impersonalization of AI systems are frequently blamed for these unfavorable responses (van Doom et al., 2022). When critical financial interactions are conducted without a human touch, some users may experience cognitive overload and a loss of trust, particularly those who are less accustomed to digital interfaces or who are financially vulnerable (Tariq et al., 2024). Additionally, Castelo et al.'s (2019) research indicates that humans are more inclined to reject AI when it comes to tasks that they believe call for moral judgment or emotional intelligence, which are still thought to be exclusively human characteristics.

In the Indonesian context, Setiawan et al. (2023) mention that the COVID-19 pandemic, financial inclusion initiatives, and smartphone penetration have all contributed to the swift adoption of digital banking. Zhou et al (2024) mention that consumers who prefer human involvement in financial decision-making, however, continue to express worries about trust, privacy, and the impersonality of AI-driven interactions. It becomes crucial to comprehend the complex reactions of various

demographic groupings in this context. As a mediator of sociopsychology, gender has a major impact on how people view technology, how much risk they can take, and how they prefer to connect with others (Setiawan, 2024). The relevance of human empathy in service delivery, openness to automation, and trust levels toward AI may vary between men and women, according to prior research (Zhang et al., 2021).

Through an examination of Indonesian customers' acceptance of AIDs in digital banking services, this study seeks to verify the AIDUA model by specifically analyzing the ways in which gender disparities alter these acceptance routes. Through the integration of cognitive and affective assessments and the examination of gender's moderating influence, this study offers empirical knowledge that can guide more inclusive and flexible AI tactics in the banking industry. In addition to providing useful implications for financial institutions looking to maximize their digital banking experience while preserving customer satisfaction, trust, and engagement across a variety of user groups, the findings are anticipated to add to the continuing conversation on human-AI collaboration in service environments.

LITERATURE REVIEW AND HYPOTHESES

Artificial Intelligence in Banking Industry

The theoretical foundation of artificial intelligence (AI), a family of technologies that includes anything from basic self-service kiosks to interactive robots, was founded more than 70 years ago, and its fundamental ideas have remained largely unaltered (Chi et al., 2020). During a symposium at Dartmouth in 1956, Minsky and McCarthy coined the term artificial intelligence (Haenlein and Kaplan, 2019).

According to Milojevic and Redzepagic (2021), artificial intelligence (AI) is the theory and computer system progress which is capable of conducting assignments and solving problems that usually need human intelligence as the prerequisite. Similarly, Kaplan and Haenlein (2019) define AI as the capacity of a system to accurately interpret external data, learn from such data, and apply those learnings to accomplish particular tasks and goals through flexible adaptation.

AI, which has undergone several stages throughout the years, is currently understood to be an entity that employs a collection of tools to automatically replicate human cognitive capacities in order to accomplish predetermined goals and raise the likelihood of success in particular tasks (Rahman et al., 2022). According to Belanche et al. (2019), artificial intelligence (AI) is a technology that revolutionizes nearly all industry's processes, from sales and service delivery to production. AI is being prioritized by the high-tech and automotive sectors, including banking, financial services, and insurance (Herrmann and Masawi, 2022).

On the other hand, an increasing amount of research offers a different viewpoint, suggesting that patrons may experience feelings of fear, anxiety, or emotional detachment when interacting with AIDs (Pitardi & Marriott, 2021; Belanche et al., 2022). Concerns about data privacy, a lack of empathy, and the apparent complexity or impersonalization of AI systems are frequently blamed for these unfavorable responses. When critical financial interactions are conducted without a human touch, some users may experience cognitive overload and a loss of trust, particularly those who are less accustomed to digital interfaces or who are financially vulnerable. Additionally, Castelo et al. (2019) indicates that humans are more inclined to reject AI when it comes to tasks that they believe call for moral judgment or emotional intelligence, which are still thought to be exclusively human characteristics.

Artificially Intelligent Device Use Acceptance Model

While TAM is the most widely used model to explain the adoption process of the new technology, it is insufficient to explain the acceptance of breakthrough technology in artificial intelligence. (Sohn & Kwon, 2020). Due to the uniqueness of AID characteristics, the power of TAM in explaining the acceptance process of this new technology has decreased, and need the new model which specific with AID (Kelly et al., 2023). In this setting, Gursoy et al. (2019) create the AIDUA model by combining the Cognitive Appraisal Theory (Lazarus, 1991) and Cognitive Dissonance Theory (Festinger, 1962).

By emphasizing concept like ease of use, Technology Acceptance Model are able to explain why the non-intelligent technology were accepted. However, since artificial intelligence mimics human intelligence, there is no need to learn how to use the device. Consequently, the adoption of AID with distinctive features cannot be adequately explained by the pertinent component of TAM. When Artificially Intelligent Device are used in service delivery, there may be both positive (when customer waiting less time), and negative (when customer loss of human interaction) effects. A circumstance like this could result in both, utilizing and not utilizing the AID.

According to the AIDUA paradigm, consumer go through a three-phase of cognitive process while deciding whether to accept or reject the use of AID. The very first step is primary appraisal and it comprises the assessment of customer regarding the social influence (SI), hedonic motivation (HM) and perceived anthropomorphism (PANT) in relation to AID (Artificially Intelligent Device). The second step is about customer's performance expectancy (PE) and perceived effort expectancy (PEE) toward AID which can influence their emotion (EM). At final stage which knows as outcome phase is willingness to accept the AID (Gursoy et al., 2019).

Hypotheses Development

Furthermore, Ding et al. (2020) showed that reference group have the power to affect the customer's attitude, beliefs and decision making. Therefore, a person likely to adopt a mindset which consistent with their group norms, if the majority of people in their social group or reference group believe that use AID will create benefits (Liu et al., 2020). Social Influence (SI) plays a significant role in determining the customer's customer willingness in the relation toward AID usage or rejection. Based on this notion, we propose this hypothesis:

H1: Social influence has significant role as predictor of willingness to use AID in digital banking service.

In the literature on technology adoption, hedonic motivation has been seen as a crucial intrinsic customer drive, making it as a major factor in determining technological acceptance (Huang & Rust, 2018; Hermann & Masawi, 2022). Thus, hedonic motivation might serve the similar purpose in relation to the process of adopting AID (Lin et al., 2020). Additionally, hedonic drive is said to be more important than utilitarian motivation when it comes to AI technology in terms of curiosity and seeking out new experiences (Sohn and Kwon, 2020). Additionally, a number of research have shown that the AI adaptation process has a strong antecedent in the hedonic motivation of customers (Gursoy et al., 2019; Roy et al., 2020; Vitezic and Peric, 2021). Customers will therefore have a favorable attitude toward AI technology if they believe they will find it enjoyable. This means that clients with high HM are more likely to think that AIDs will help them and are less likely to care about the work involved in

using them. Based on these notions, we proposed following hypotheses to be examined:

H2: Hedonic motivation has significant role as predictor of willingness to use AID in digital banking service.

Performance Expectancy is the extent to which a user thinks that utilizing an AI tool will increase the efficacy and efficiency of services. Performance Expectancy has been shown to improve the user attitude in a number of studies. Pillai & Sivathanu (2020) and Pande & Gupta (2022) discovered that customer who believe in AI to be accurate and efficient will form a positive opinion about the application in service environment. However, previous research also has shown that difficult task which require the human-like judgement place the AID useless (Goudey & Bonnin, 2016; Ghazwani et al., 2022). Based on these arguments, we propose following hypotheses to be tested:

H3: Performance expectancy has significant role as predictor of willingness to use AID in digital banking service

Intrusiveness related to the extent of AID is perceived as invasive and can be disrupt the personal boundaries and human privacy. Therefore, as proven by Belanche et al (2022), Pitardi & Marriot (2021) and also Hamid & Nigam (2022), customers may feel discomfort or mistrust when AID collect personal information and operate without clear control from the users. Such perceived intrusiveness tends to negative attitude. However, other study conducted by Zhu & Chang (2020) and Zhang et al. (2021) suggest that younger digitally literate user may overlook the privacy concerns if the perceived utility is high. Therefore, we proposed following hypotheses to be tested.

H4: Perceived intrusiveness has significant role as predictor of willingness to use AID in digital banking industry.

Gender differences is well known term in consumer behavior and technological acceptance research field. These disparities can have a big impact on how people making assessment and accept the new technology especially artificially intelligent by different cognitive processing style, emotional reaction and perceived risk between man and woman. Previous studies have repeatedly demonstrated that males tend to interact with technology in a more utilitarian and task-oriented manner when viewed through the lens of cognitive assessment. Men are more prone than women to base their views and intentions on performance expectancy, or the conviction that a system would increase productivity, effectiveness, or efficiency (Prebensen & Rosengren, 2016; Northey et al., 2022). Thus, we propose the gender differences as moderator variable in this research, and examine following hypotheses:

H5: Gender difference has a significant role as a moderator between social influence and willingness to use AID in digital banking service.

H6: Gender difference has a significant role as a moderator between hedonic motivation and willingness to use AID in digital banking services.

H7: Gender difference has a significant role as a moderator between performance expectancy and willingness to use AID in digital banking service.

H8: Gender difference has a significant role as a moderator between perceived intrusiveness and willingness to use AID in digital banking services.

METHOD

This research uses a quantitative explanatory research design to examine consumer acceptance of AID in digital banking services. The study especially looked at how customer behavioral intentions are affected by three cognitive appraisals which consist of performance expectancy, intrusiveness, and emotional value. It also looked at how gender had a moderating role in these effects and social influence as group reference. Customers of digital banking in Indonesia who have previously interacted with AIDs, such as chatbots or virtual assistants integrated into digital banking platforms, are the most suited respondents for this research chosen using a purposive sample technique (El-Shihy et al., 2024).

A total of 96 valid responses, are collected via online survey platform, powered by Google Form after screening of the missing response. Multiple assessment questions that were modified from validated instruments in prior research made up the structured questionnaire used to collect the primary data. Every item was scored on a 5-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree." Using four items modified from Gursoy et al. (2019) and Lu et al. (2020), performance expectancy was assessed. Four items based on research by Belanche et al. (2022) and Pitardi and Marriott (2021) were used to measure intrusiveness. The study used three questions derived from Davis (1989) and Gursoy et al. (2019) to measure behavioral intention, and four items adapted from Gursoy et al. (2019) and Belanche et al. (2022) to measure emotional value. Male or female gender was noted as a categorical variable.

Email invitations and the researcher's private database were used to gather data online. Respondents were made aware of the study's goal, and participation was anonymous and voluntary. SmartPLS 4.0 software is used to analyze the data using Partial Least Squares Structural Equation Modeling (PLS-SEM). According to Hair et al. (2014), this approach was selected because it is robust when working with small-to-medium sample sizes and is appropriate for evaluating complicated models that include both reflective and formative aspects. Cronbach's alpha, composite reliability, cross loading score, and Average Variance Extracted (AVE) are used to assess the validity and reliability of the measurement model (Hair et al, 2019). For the structural model, this study bootstraps with 5,000 subsamples to test the significance of the hypothesized paths (Hair et al., 2021).

To evaluate the reliability of internal consistency, Cronbach's Alpha was employed. An acceptable threshold value was 0.70 or more, which shows that the indicators in a construct accurately measure the same hidden variable. In exploratory research settings, ratings below 0.60 indicate poor dependability, whereas values between 0.60 and 0.70 may still be considered adequate. However, redundancy among items may be indicated by values more than 0.95 (Hair et al., 2022).

Since Composite Reliability (CR) does not imply equal indicator loadings (tau-equivalence), it was also assessed as a more reliable indicator of internal consistency, especially when used with PLS-SEM. In the early stages of study, values between 0.60 and 0.70 can be accepted, but a CR value of 0.70 or greater was deemed acceptable (Fornell & Larcker, 1981; Hair et al., 2022). The Average Variance Extracted (AVE) was used to evaluate convergent validity. AVE shows the percentage of variance that a construct capturing compared to the variance caused by measurement error. According to Fornell and Larcker (1981), the construct had to explain more than half of the variance in its indicators with an AVE value of at least 0.50. A value less than 0.50 would indicate that the model needs to be revised and that the convergent validity is insufficient.

In assessing the structural model, several statistical parameters and threshold criteria are employed to evaluate the hypothesized causal relationship among the latent construct. The path coefficients represent the strength and direction of the relationships between the independents and dependent variables, with higher absolute values indicating the stronger effects. The significance of each path is determined using a bootstrapping procedure with 5000 subsamples, which is recommended to ensure the robust estimation of standard error in PLS-SEM. The resulting t-values and p-values are comparing against conventional threshold, where a t-value of 1.96 or higher indicates significance at the 5% level and t-value more than 1.64 represents significance at the level 10%. In addition, the coefficient of determination is used to assessed the explanatory power of the model with values of 0.75, 0.50 and 0.25 are considered substantial, moderate and weak respectively.

RESULTS AND DISCUSSION

Data from 99 respondents in Indonesia's largest cities—Jakarta, Semarang, and Surabaya are gathered for this study in order to investigate how bank customer view and react to the artificial intelligence device in digital banking. Participants consist of 52.2% men and 47.8% women. Most of them (65.5%) had at least an undergraduate degree and had used AI-driven banking apps before. This demographic distribution makes it possible to conduct a thorough investigation of the ways in which gender and generational perspectives influence the behavioral intention, emotional response, perceived utility, and intrusiveness of AID use in banking.

Validity and Reliability Test Result

Average Variance Extracted (AVE) and individual item loadings are assessed as a part of the validity analysis for the Social Influence construct. As can be seen in Table 1, three items (SI1, SI2, and SI5) have values of 0.978, 0.952, and 0.950, respectively. This is indicating substantial outer loadings over the generally recognized cutoff of 0.50. These metrics exhibit outstanding convergent validity, suggesting that they accurately capture the hidden variable Social Influence in relation to AI device in digital banking service.

Nevertheless, the items of SI3 and SI4 are the only items that have cross loadings. It means that they loaded more strongly on other constructs than on the intended latent variable. According to this result, there may be conceptual ambiguity or overlap with other model variables (such as perceived value or behavioral intention) if these two items are not exclusively linked to the social impact dimension. Cross-loading items can erode the clarity of measuring a construct and jeopardize discriminant validity if they are kept.

The construct's Average Variance Extracted (AVE) was 0.57, over the required minimum of 0.50 (Fornell & Larcker, 1981), notwithstanding these reservations. Indicating significant convergent validity at the construct level, this shows that the social impact construct accounts for over 50% of the variation of the indicators on average. It is advised to take SI3 and SI4 out of the final measurement model in light of this outcome. They might introduce conceptual noise or multicollinearity, based on their cross-loading behavior. Given that the remaining three indicators (SI1, SI2, and SI5) exhibit high reliability and representativeness, removing them could enhance the discriminant validity and overall parsimony of the model.

Excellent results are obtained from the validity check of the Hedonic Motivation construct. Strong correlations with the latent variable are indicated by the outer loading values of all four indicators (HM1 through HM4), which are over 0.95. This

indicates that the products regularly gauge how much fun and delight using AI in digital banking is. With an Average Variance Extracted (AVE) of 0.913, which is significantly higher than the allowed minimum of 0.50, excellent convergent validity is confirmed. All four indicators can be kept in the model, and the Hedonic Motivation construct has been thoroughly tested.

Results from the Performance Expectancy construct's validity test are not entirely consistent. Reliability as measures of the construct is demonstrated by the extremely strong outer loadings of two indicators (PE1 = 0.934 and PE2 = 0.954). The relatively strong PE3 (0.729) and the near-acceptable loading threshold (≥ 0.50) PE4 (0.530) indicate a modest contribution to the construct. Convergent validity is generally deemed adequate, as evidenced by the Average Variance Extracted (AVE) of 0.512, which is slightly above the necessary cutoff of 0.50 (Fornell & Larcker, 1981).

The validity of perceived intrusiveness is very good. With outside loadings ranging from 0.931 to 0.976, all four indicators (PI1 through PI4) exhibit extremely high values that much above the typical cutoff of 0.70. This suggests that every item accurately captures the fundamental concept. Additionally, the Average Variance Extracted (AVE) is 0.922, which is a considerable increase over the 0.50 minimal requirement and confirms exceptional convergent validity.

Four reflecting indicators are used to measure this construct; each one reflects a distinct behavioral action toward engaging with AI device in digital banking service. For every indication, the outer loading values fall between 0.956 and 0.973, well beyond the 0.5 minimum criterion and even the stricter 0.7 cutoff that is frequently employed in structural equation modeling. These high loading values establish outstanding convergent validity by showing that each item has a strong association with the latent variable it is meant to assess. The indicators show consistency and clarity in gauging users' desire to embrace and interact with AI device in digital banking service.

Table 1
Validity Check Result for Social Influence

No	Item	Indicator	Outer Loading T-values	Average Variance Extracted	Parameter Used
1	Using AI devices in banking service reflects my status symbol in my social network (friends, family and co-workers)	SI1	0,978	0,57	>0,5
2	People who influence my behavior want me to use AI devices in banking service	SI2	0,952		
3	People in my social networks who use AI device have more prestige than those who don't	SI3	Crossed Loading		
4	People who are important to me will encourage me to utilize AI device in banking service	SI4	Crossed Loading		
5	People in my social networks whi will utilize artificially intelligent banking service have a high profile	SI5	0,950		

Source: Processed Primary Data, 2025

Table 2
Validity Check Result for Hedonic Motivation

No	Item	Indicator	Outer Loading T-values	Average Variance Extracted	Parameter Used
1	I have fun interaction with AI in banking service	HM1	0,963	0,913	>0,5
2	Interacting with AI device is fun in banking service	HM2	0,958		
3	Interacting with AI device is entertaining in banking service	HM3	0,965		
4	Interacting with AI is enjoyable in banking service	HM4	0,959		

Source: Processed Primary Data, 2025

Table 3
Validity Check Result for Performance Expectancy

No	Item	Indicator	Outer Loading T-values	Average Variance Extracted	Parameter Used
1	Banking service provided by AI devices are more accurate than human beings	PE1	0,934	0,512	>0,5
2	Banking service provided by AI devices are more accurate with less human errors	PE2	0,954		
3	AI devices provide more consistent banking service than human beings	PE3	0,729		
4	In banking service, information provided by AI device are more consistent	PE4	0,530		

Source: Processed Primary Data, 2025

Table 4
Validity Check Result for Perceived Intrusiveness

No	Item	Indicator	Outer Loading T-values	Average Variance Extracted	Parameter Used
1	I feel that the AI-based digital banking service invades my personal space	PI1	0,931	0,922	>0,5
2	The AI assistant in the digital banking service makes me feel like my privacy being violated	PE2	0,971		
3	The presence of AI in banking interaction feels overly interfering	PE3	0,975		
4	The AI system tries to control too much of my decision making process	PE4	0,976		

Source: Processed Primary Data, 2025

Table 5
Validity Check Result for Willingness to Use AID

No	Item	Indicator	Outer Loading T-values	Average Variance Extracted	Parameter Used
1	I'm willing to receive AI device banking service	Int1	0,959	0,932	>0,5
2	I'm will feel happy to interact with AI device in banking service	Int2	0,956		
3	I'm likely to interact with AI device in digital banking service	Int3	0,973		
4	I'm willing to adopt the AI device in digital banking service	Int4	0,959		

Source: Processed Primary Data, 2025

As shown in Table 6, the reliability check is conducted to ensure that each construct in the measurement model consistency measures what it is intended to measure. Reliability testing in this research includes three main parameters, namely Cronbach's Alpha, Composite Reliability, Average Variance Extracted, which are standard parameters in Partial Least Square analysis. Cronbach's Alpha assesses the internal consistency of items within the construct, where a value of 0.70 or higher is generally considered acceptable, and indicates that the indicators' reliability represent the latent variable.

Meanwhile Composite Reliability is a more robust measure of reliability in PLS-SEM because it does not assume equal indicator loading. CR values between 0.70 and 0.95 indicate satisfactory reliability, while values above 0.95 may suggest redundancy among items. The Average Variance Extracted is used to evaluate the convergent validity, reflecting the extent to which a construct explains the variance of its indicators. An AVE value of 0.50 or higher suggest that the construct explains at least 50% oth the variance in its observed variables.

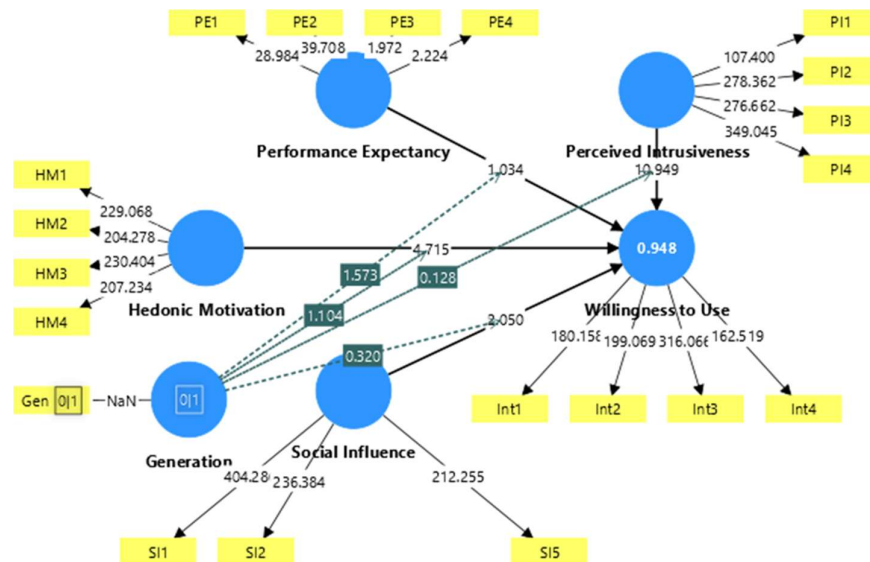
Table 6
Reliability Check Result for All Construct

No	Item	Composite Reliability	Cronbach's Alpha	Parameter Used
1	Social Influence	0,953	0,715	>0,5
2	Hedonic Motivation	0,973	0,974	
3	Performance Expectancy	0,863	0,546	
4	Perceived Intrusiveness	0,974	0,974	
5	Willingness to Use AID	0,973	0,973	

Source: Processed Primary Data, 2025

Path Analysis and Hypotheses Test Result

Partial Least Squares Structural Equation Modeling (PLS-SEM) is the main analytical technique used in this work to assess the measurement and structural model. PLS-SEM provides a strong and adaptable framework to assess the causal links and the model's measurement quality, here is the path analysis result as shown in Figure 1 and Table 7 below



Source: Processed Primary Data, 2025

Figure 1
Path Analysis Result

Table 7
Path Analysis and Hypotheses Testing

No	Independent Construct	Dependent Construct	T-Statistic	Parameter Used	Result
1	Social Influence	Willingness to Use AID	2,05	>1,96	Significant
2	Hedonic Motivation		4,715		Significant
3	Performance Expectancy		1,034		Less Significant
4	Perceived Intrusiveness		10,949		Significant
5	Generation x Social Influence		0,320		Less Significant
6	Generation x Hedonic Motivation		1,104		Less Significant
7	Generation x Performance Expectancy		1,573		Less Significant
8	Generation x Perceived Intrusiveness		0,128		Less Significant

Source: Processed Primary Data, 2025

As shown in Figure 1 and Table 7, the analysis reveals that among the eight tested hypotheses, only three paths are statistically significant at the 5% level ($t > 1.96$). Specifically, Social Influence toward Willingness to Use AID (with t-statistic value is 2.05), Hedonic Motivation toward Willingness to use AID (with t-statistic value is 4.715), and Perceived Intrusiveness toward Willingness to use AID (with t-statistic value is 10.949) show significant effects. In contrast, Performance Expectancy is not significant affect the Willingness to use AID (with t- statistic value is 1.034), suggesting the perceived usefulness alone does not strongly predict the adoption behavior in this context. Furthermore, all moderating effects involving Generation (Gen Y and Z) are found to be statistically insignificant. This implies that generational differences does not meaningfully alter the relationship between the antecedents variables and willingness to use AID.

CONCLUSION AND SUGGESTION

The main dependent variable, Willingness to Use AI devices in digital banking services, is tested by using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the effects of five constructs which are Performance Expectancy, Hedonic Motivation, Perceived Intrusiveness, Social Influence, and Generation as moderation. The Willingness to Use construct's R² value suggests a very good model that accounts for almost 94.8% of the variance in user willingness. According to the analysis, consumers' willingness to utilize AI devices (AID) in digital banking is highly influenced by hedonic motivation, social influence, and perceived intrusiveness. Performance expectancy and other generational moderation effects are shown to be statistically not significant. These findings are explained in the context of earlier empirical studies conducted during the past ten years (Boustani, 2021; Berger et al., 2021).

Hedonic Motivation is found to be a significant predictor, which is in line with new research that highlights the significance of emotional experience and enjoyment in technology use. According to studies by Chatterjee et al. (2021) and Hamzah et al. (2022), users are more likely to embrace AI devices if they feel the interaction to be intuitive and pleasurable. This implies that users of digital banking react favorably to AI devices that provide both utility and user happiness through captivating user interfaces, including gamified features or conversational agents. Emotional intelligence, customization, and engaging user experiences are practical ways that banks may improve AI capabilities to boost user attachment and retention.

Another factor that was statistically significant was Social Influence. Studies like Oliveira et al. (2016) and Alalwan et al. (2017) made clear importance of social media opinions, family recommendations, and peer pressure are in determining how customers behave online. According to Laukkanen and Kyriakos (2023), social norms have a particularly significant influence in collectivist societies, such those seen in Southeast Asia. This research implies that in order to encourage AI adoption through a community effect, digital banks should strategically employ peer referral systems, influencer alliances, and social marketing.

There was the greatest adverse effect on readiness to adopt AI device from perceived intrusiveness. Recent privacy-related research (Shin & Park, 2017; Liébana-Cabanillas et al., 2023) have highlighted the detrimental effects of invasive or opaque AI methods on consumer trust, especially in the financial services industry. Users' concerns about data tracking, surveillance, and unjustified automated conclusions are growing. In practice, banks need to make sure that their AI device communicate openly, don't violate data protection laws, and let users choose whether or not to employ personalization capabilities.

Although Performance Expectancy is not statistically significant, it was in line with more recent findings from Marakarkandy et al. (2017) and Al-Saedi et al. (2021), which imply that users already expect a baseline of functional efficiency in mature digital markets. This is in contrast to traditional acceptance models like UTAUT (Venkatesh et al., 2003). In these situations, unless AI performance gains are very differentiated, they might not be seen as a unique value. Banks must therefore highlight how AI elements in particular improve automation, decision-making, and predictive services beyond traditional digital platforms.

The moderating effects of gender on all four core relationships which is social influence, hedonic motivation, performance expectancy, and perceived intrusiveness) are found to be non-significant moderator. This contrasts with earlier assumptions that generational traits significantly affect technology adoption (Prensky, 2015). However,

more recent studies (Nguyen et al., 2023; Rahi et al., 2021) have shown that the digital divide is narrowing, with all age cohorts becoming increasingly comfortable with technology due to broader digital exposure and financial inclusion efforts. Practically, this implies that banks can adopt a unified digital engagement strategy that targets shared values like trust and emotional engagement, rather than only rely on generational customization.

This study has limitations despite its excellent findings. In order to test the study model, a cross-sectional methodology was used, which restricts the capacity to record shifts in consumer opinions or behaviors across time. Given the dynamic and quick evolution of technology acceptability, particularly in relation to artificial intelligence (AI), longitudinal research might be helpful in understanding how user willingness to use AI devices in digital banking varies across various technological maturity levels. Besides, although the study includes important concepts like perceived intrusiveness, social impact, and hedonic incentive, it omitted other pertinent environmental or psychological elements like trust, perceived danger, technology anxiety, or AI literacy. Future studies could offer a more thorough understanding of the factors that precede the adoption of AI devices by incorporating these variables, especially in delicate industries like banking where security and trust are crucial.

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