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Evaluating User Satisfaction in AI-Powered Digital Banking: An Expectation Confirmation Model Approach

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Abstract

This study aims to analyze user satisfaction with artificial intelligence (AI)-based digital banking services by integrating AI features into the Expectation Confirmation Model (ECM). The study used a quantitative approach with data collected through questionnaires distributed to 124 bank customers in Indonesia who have used AI-based banking services. Data were analyzed using the Partial Least Squares–Structural Equation Modeling (PLS-SEM) method. The results showed that expectation confirmation had a positive and significant effect on perceived performance, but a negative effect on user satisfaction. Meanwhile, perceived performance did not have a significant effect on user satisfaction. Furthermore, AI features including trendiness, visual attractiveness, problem-solving ability, and customization were shown to have a positive and significant effect on user satisfaction. Conversely, communication quality did not have a significant effect on user satisfaction. These findings indicate that user satisfaction with AI-based banking services is influenced not only by meeting expectations, but also by the service's ability to provide engaging, personalized, and effective experience in addressing user needs. Therefore, digital banking service providers need to prioritize the development of these aspects to increase user satisfaction and strengthen their experience of using AI-based services.

Keywords: AI-digital banking, user satisfaction, AI features, expectation confirmation model, PLS-SEM

1. Introduction

The digital transformation is presently sweeping the world and is the main cause of extraordinary changes in innovation in various sectors of society (Mi Alnaser et al., 2023). Technological development has significantly impacted various aspects of life, from how we work, learn, shop, and engage with people. One of the positive impacts of digital transformation is improved access and connectivity for the community. Through the internet and digital technology, people can now access information, services, and opportunities that were previously unreachable.

The banking industry has entered a revolutionary digital transformation era, driven by rapid technological developments and shifting consumer preferences. In this era of Economy 4.0, digital banking is not just a trend, but has become a fundamental need to maintain competitiveness and relevance in an increasingly enthusiastic market. By adopting cutting-edge technologies including artificial intelligence (AI), big data, cloud computing, and blockchain, digital banking can fundamentally change the financial landscape, open up new opportunities, and foster a more inclusive and sustainable financial ecosystem.

AI is swiftly revolutionizing the financial ecosystem inside the banking industry, profoundly altering operational processes, client experiences, and company strategies across several financial domains. Technological developments and the increasing need for sophisticated technology force banks to adopt technology rapidly (Maja & Letaba, 2022). Artificial intelligence (AI) in banking has evolved into advanced systems capable of analyzing diverse data and producing responses that closely emulate human interaction. AI-driven banking solutions aggregate data from multiple digital and physical sources, process and learn from it, and efficiently resolve customer inquiries and complex issues (Haenlein et al., 2019; Xu et al., 2020). The integration of AI enables banks to increase service quality to better meet customer needs and expectations.

AI has profoundly transformed the banking sector, especially in autonomous knowledge management (Omoge et al., 2022). A McKinsey Global Institute report highlights how machine learning and AI significantly enhance risk management, sharpen decision-making, and deliver personalized services (Babel et al., n.d.). According to Statista data from 2023, globally, there has been a steady rise in AI adoption within finance since 2022, with continued expansion forecasted through 2025. By 2022, 46% of companies worldwide had implemented AI, and about 43% are expected to deploy AI in services by 2025. This underscores the sector's commitment to continually advancing and investing in AI to enhance service quality. The McKinsey report further notes that nearly 60% of banks have integrated AI, notably in fraud detection, virtual assistants, and real-time risk monitoring (Biswas et al., 2020).

Integrating AI in banking has transformed traditional banking methods towards increased efficiency and innovation focusing on clients. AI in the banking and finance sector provides a significant transformation in the way financial services and banking operate. Modern digital banking services powered by AI include facial recognition, chatbots, atomization of cybersecurity detection, biometric authentication, humanoid robots and others (Al-Okaily et al., 2025).

The fundamental comprehension of AI-enabled digital banking has been the focus of countless studies. Mogaji et al. (2021) stated that AI has the potential to improve consumer engagement in the banking sector, and as a result, theoretical knowledge on the subject should be improved. Omoge et al. (2022) conducted an additional study that demonstrated that AI-enabled digital banking improves consumer experience and has a beneficial effect on consumer purchasing behavior. However, the investigation is deficient in its examination of the specific type of AI that can improve consumer experience.

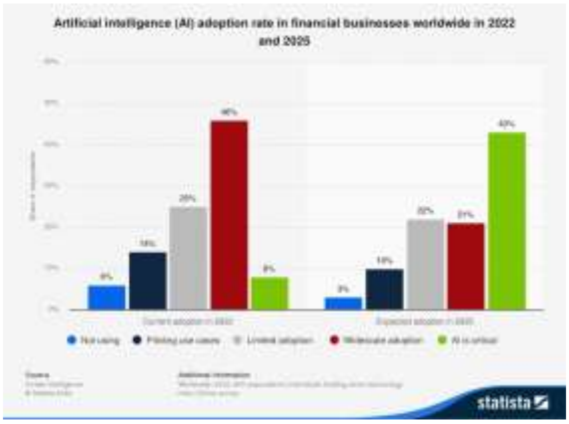

Figure 1. AI Adoption rate in Financial Businesses

Source: Statista (2025)

This study investigates consumer satisfaction with digital banking by developing a combined model integrating AI determinants with the Expectation Confirmation Model (ECM). Building on the work of Mi Alnaser et al. (2023), this study extends the existing literature on user satisfaction in digital banking by addressing two important gaps. First, previous studies conducted in Pakistan examined digital banking users as a homogeneous population without distinguishing between generational groups. In contrast, this study focused exclusively on Generation Y (Gen Y), a group of digital natives characterized by higher technological adaptability and more critical expectations for AI-enabled banking services than previous generations.

Second, Indonesia is one of the most dynamic fintech and digital banking markets in Southeast Asia (OJK, 2025), where intense digital competition and rapid AI adoption may shape user expectation confirmation and satisfaction differently than other contexts. Therefore, testing the integrated ECM in the Indonesian digital banking environment provides additional empirical evidence regarding the role of AI in influencing customer satisfaction under a highly competitive digital ecosystem.

2. Literature Review

2.1 Expectation Confirmation Theory (ECT)

Expectation Confirmation Theory (ECT) was initially developed in marketing to analyze customer satisfaction and the decision-making process of consumers (Oliver, 1980). ECT suggests that consumer satisfaction is driven by beliefs/disbeliefs that result from evaluating performance against expectations (Oliver, 1980). The basic concepts of ECT theory can be explained in the following steps: formation of expectation, interaction and experience, confirmation or disconfirmation, and cognitive adjustment (Hossain & Quaddus, 2012). Formation of Expectation: Consumers build initial expectations about a particular product/service before purchasing based on prior information and experience. This knowledge is acquired through various mass media platforms, peers, and influencers. Mass media is a significant source of information and understanding about products for consumers, who build expectations based on advertising, media reports, and other forms of media exposure. In addition, direct channels such as personal selling, opinion leaders, peers, and influencers influence consumers' knowledge and expectations about products. When consumers have access to accurate product information, they form realistic expectations. However, if such information spreads, it leads to unrealistic expectations.

Interaction and Experience: Consumers purchase and use products after carefully considering the information. After consumers use the product, they form perceptions about its performance. Confirmation or Disconfirmation: Consumers judge the perceived performance of the product (or service) based on their initial expectations. Three possibilities can lead to disconfirmation. First, perceived product performance > expectations = positive disconfirmation; second, perceived product performance < expectations = negative disconfirmation; and third, perceived product performance = expectations = simple confirmation.

Cognitive Adjustment: Based on the confirmation of their expectations, consumers form a level of satisfaction. Positive disconfirmation and simple confirmation strengthen the consumer's attitude toward the product, leading to satisfaction (Oliver & DeSarbo, 1988). In the case of negative disconfirmation, consumers develop an unfavourable attitude toward the product, leading to dissatisfaction. Consumers who are satisfied with the product's performance are more likely to repurchase the product than dissatisfied consumers. In some cases, even dissatisfied consumers are forced to repurchase the product, due to the lack of viable alternatives or high switching costs. Similarly, all satisfied consumers may not repurchase the same product, due to intrinsic factors such as variety-seeking behaviour, need for uniqueness, or innovation (McAlister & Pessemier, 1982).

ECT is extensively utilized by researchers to assess customer satisfaction and post-purchase intentions about products, services, and technologies (Hossain & Quaddus, 2012) In this study, ECT theory is used to evaluate digital banking user satisfaction with the implementation of AI.

2.2 Artificial Intelligence in Banking

Artificial intelligence (AI) spans many disciplines and has varied meanings across scientific fields. For computer scientists, AI means designing programs with intelligent behaviors like planning or language translation. Engineers use AI to build machines that handle human tasks, from ATM recognition to advanced robots for exploration or automation. Cognitive scientists leverage AI to study and model human intelligence and behavior.

A consensus on a singular definition of artificial intelligence (AI) is lacking due to its broad scope. Monett et al. (2020) note that academics have not reached consensus on a general definition. In 1956, John McCarthy, Marvin Minsky, and colleagues at Dartmouth defined Artificial Intelligence as "the science and engineering of creating intelligent machines" (Monett et al., 2020).

International financial institutions and committees consider rapidly evolving technologies, including artificial intelligence (AI), to be main drivers in accelerating the growth and personalization of financial services. In 2017, the Financial Stability Board (FSB), an international organization responsible for monitoring and providing recommendations on the stability of the world financial system, highlighted various applications of AI in the finance, including portfolio management, customer due diligence, credit risk assessment, and regulatory compliance. The FSB also noted that AI can provide significant benefits to retail clients and small to medium-sized organizations (SMEs), while also improving banks' operational efficiency. Furthermore, a 2018 report by the Basel Committee on Banking Supervision (BCBS), a global banking supervisory authority and prudential standards setter, encouraged banks to adopt innovative technologies such as AI to enhance their capabilities in risks management related to the development of fintech.

Generative AI is driving transformative change across the Banking, Financial Services, and Insurance (BFSI) industry, in principle reshaping operations within key sectors. Transactional processes are streamlined by automating routine tasks, accelerating workflows while minimizing human error. In customer interactions, AI delivers deeper personalization, resulting in more relevant experiences and increased satisfaction and loyalty. In the credit sector, AI models enable more accurate risk evaluation and expedite decision-making, broadening access to credit and lowering default risk. Additionally, the security sector benefits from AI, which detects and counters suspicious activity in real-time, fostering a proactive and resilient risk management environment.

In the investment sector, AI is transforming algorithmic trading by enabling the deployment of more advanced strategies and enhancing the effectiveness of portfolio management. Moreover, this technology is assuming a pivotal role in regulatory compliance by automating the surveillance and reporting of financial activities, thus streamlining adherence to increasingly complex regulations. While offering new opportunities, AI adoption also introduces challenges, such as concerns over personal data privacy, model reliability, and the ethical implications of AI-driven decisions. Despite these obstacles, integrating Generative AI into the BFSI industry promises substantial benefits, including heightened operational efficiency, service innovation, and sharper customer focus. As this technology advances, it is essential for the financial sector to proactively address associated risks and challenges to secure long-term gains.

According to a McKinsey working paper (2020), the integration AI in banking delivers four principal benefits: higher profitability, deep service personalization, growth into omnichannel markets (such as e-commerce platforms), and accelerated organizational innovation. The study also notes that nearly 60% of major banks have adopted AI in their workflows. Most institutions leverage AI for virtual assistants (like customer service chatbots), fraud detection, and real-time risk analysis. Overall, AI's presence has profoundly affected the banking sector, enhancing performance at three levels: (i) operational processes, (ii) products and services, and (iii) the experiences of customers and staff.

2.3 Hypothesis Development

2.3.1 Expectation confirmation and user satisfaction

The Expectancy Confirmation Theory (ECT) emphasizes that users form expectations about a product/service before use, which are then compared to their post-use experiences. If initial expectations are met, positive confirmation occurs, which drives user satisfaction. Negative disconfirmation transpires when expectations are unmet, leading to dissatisfaction (Oliver, 1980).

In the context of AI-based banking services, users have expectations related to system reliability, ease of use, data security, service personalization, and efficiency. When these features function according to or exceed expectations, users perceive real benefits from AI technology, which in turn increases user satisfaction with the service. Conversely, the failure of AI to provide a smooth, responsive, or accurate user experience can lead to disconfirmation of expectations, which is detrimental to users' perceptions of the overall digital banking service and AI. User satisfaction here reflects not only rational evaluations but also emotional components of the user experience.

Previous studies support this relationship. Research by Bhattacherjee (2001), Qin & Xu (2007), indicated that expectation confirmation has a positive effect on user satisfaction in various technology-based systems. This also applies in the context of digital banking systems, which increasingly rely on AI technology to enhance service quality. Therefore, this relationship serves as the foundation for the initial hypothesis: "H1 Confirmation of expectations positively influences user satisfaction."

Then, expectation confirmation also affects how users perceive the actual performance of a product/service. When expectations are confirmed, users tend to interpret product performance positively because it aligns with their initial expectations. Conversely, unmet expectations can cause users to view the performance less favorably, regardless of the product's objective quality (Bhattacherjee, 2001). For example, if users expect an application to make their work easier and this expectation is met, they will evaluate the application's performance positively. Thus, the second hypothesis can be formulated: "H2 Expectation confirmation positively influences user-perceived performance."

User satisfaction is the result of a subjective evaluation of their experience when using a system or service, and this is greatly influenced by their perception of the service's performance (Zhou & Liu, 2014). When users feel that the service runs as expected in terms of speed, reliability, and efficiency, their satisfaction tends to increase. According to Alalwan et al. (2016), in the context of digital services, high-performance perceptions, such as ease of use and perceived real benefits, contribute significantly to user satisfaction. This research is in line with the results of Tam et al. (2020), who stated that performance perceptions mediate the association between initial expectations and actual satisfaction, particularly in the context of digital-based technology platforms. Therefore, the proposed hypothesis: "H3 Perceived performance positively influences user satisfaction."

2.3.2 Artificial intelligence features and user satisfaction

AI plays an essential role in transforming digital services, including those in the banking sector. AI not only increases efficiency but also creates a more personalized user experience that suits the modern digital lifestyle (Saadatmanesh, 2023). Features such as intelligent chatbots, recommendation systems, and real-time anomaly detection have made digital banking services more relevant and attractive to customers (Ramadhani & Trimuliani, 2024).

According to Saadatmanesh (2023), the current generation of users, especially young people, exhibit a greater propensity to select technology-based services that are adaptive to trends and lifestyle changes. They are interested in services that are not only functional but also reflect digital values such as speed, convenience, and innovation. Thus, the adoption of AI that follows trends is not just a complement but an important part of the customer experience strategy. Prior studies have shown that digital banking driven by artificial intelligence aligns with customer needs and contemporary lifestyles, thus enhancing user satisfaction (Godey et al., 2016; Huang & Rust, 2021). This indicates that following relevant AI trends can strengthen user loyalty and engagement towards digital banking services. Therefore, the fourth hypothesis is:

"H4 AI trends are positively influences user satisfaction."

As the use of AI-based technology increases, the visual aspect of the digital interface (UI) becomes a critical determinant in shaping users' perceptions of service quality. Visual elements, such as attractive layouts, balanced colors, luminous icons, and interactive animations, can make a positive aesthetic impression and enhance the user experience (Thwairan, 2024). An aesthetically designed interface can enhance emotional comfort and perceptions of trust in digital services, particularly in the banking context, where compliance and convenience are paramount (Ngo et al., 2025). Attractive visual design has also been shown to foster a sense of satisfaction and strengthen digital customer loyalty, as shown by research by Hoffman & Novak (2018).

Furthermore, a recent study by Paluch & Wittkop (2023) highlights that interactive and aesthetically designed AI interfaces can foster deeper emotional connections, thereby enhancing the relationship between users and digital services. This emphasizes the importance of visual quality in the development of AI-based systems, not only as technical support but as a strategy to create value and increase user satisfaction (King et al., 2020; Wu et al., 2022). Based on the descriptive basis and empirical findings, the fifth hypothesis is formulated: "H5: AI visual appeal positively influences user satisfaction."

A primary advantage of artificial intelligence-based technology is its capability to solve user problems efficiently and precisely. When users encounter obstacles in the digital service process, an AI system that can provide instant solutions, such as through responsive chatbots or personal virtual assistants, directly contributes to increased satisfaction (Ruan & Mezei, 2022). According to Mirbabaie et al. (2022), AI designed with the ability to understand the context of questions and provide relevant answers or suggestions will enhance users' perceptions of the system's reliability and usefulness. A fast and minimally inhibiting problem-solving experience creates emotional comfort, which in turn increases the overall service value.

In the digital banking sector, AI's ability to provide 24/7 assistance and respond to various types of user questions automatically creates a perception of responsive and solution-oriented service. This is considered very important in the context of a digital lifestyle that demands speed and convenience (Kim et al., 2016). Thus, effective problem-solving through AI not only improves operational efficiency but also has a positive impact on user satisfaction. Thus, the sixth hypothesis is: "H6 AI problem-solving positively influences user satisfaction."

In modern digital banking services, the ability of the system to customize services to the specific preferences and needs of users is very important. Artificial intelligence (AI) technology allows for real-time service customization, such as providing relevant financial product recommendations, delivering appropriate transaction alerts, and offering financial management advice based on previous user behavioral data (Chung et al., 2020). The ability of AI to deliver services that feel personalized can create an emotional closeness between users and service providers. According to a study by Andrade & Tumelero (2022), when users feel that digital services are specifically designed for them, satisfaction levels tend to increase because the service is considered more useful, efficient, and personally meaningful.

Customization also enhances user perceptions of service quality and fosters stronger, long-term relationships between customers and companies. In the context of digital banking, AI features that can customize interfaces and content based on user preferences have been shown to improve the experience and convenience of interacting with the system (Chen et al., 2021). Thus, the seventh hypothesis proposed is: H7 AI customization features positively influence user satisfaction.

In an AI-driven digital banking system, the quality of communication is a crucial factor influencing user perception and satisfaction. Communication quality denotes the degree to which digital service agents are able to convey accurate, reliable, efficient, and solution-oriented information while helping users save time when accessing services (Andrade & Tumelero, 2022).

Content-rich and relevant communication is essential in reducing user uncertainty. When the information provided by an AI system, such as a chatbot or virtual assistant, is accurate and easy to understand, users tend to feel more comfortable and satisfied with the service received (Arora et al., 2023). This is also supported by the finding that good communication quality contributes to building positive relationships between customers and service providers.

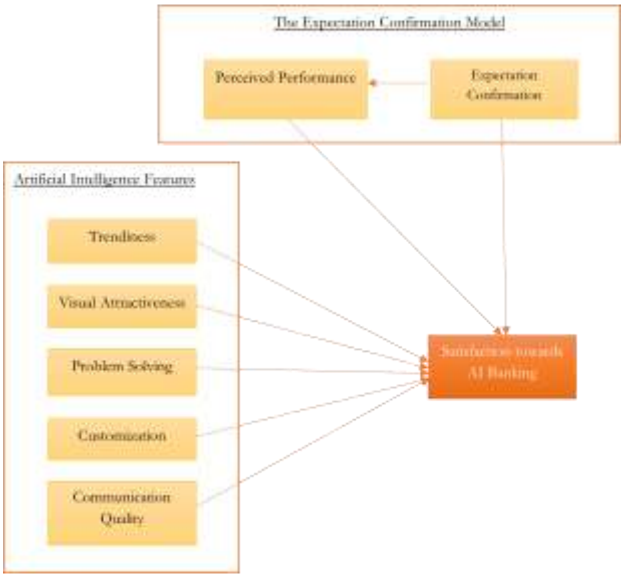

Figure 2: Research Framework

In the context of AI-based banking, effective communication through digital service agents has been shown to strengthen trust, reduce the need for face-to-face interactions, and provide a pleasant service experience. Previous studies have shown that when consumers feel they receive quality communication from AI systems, they are more likely to enjoy and persist in utilizing digital banking services (Mi Alnaser et al., 2023; Zungu et al., 2025). Therefore, the eighth hypothesis proposed by the researcher is: "H8 AI communication quality features positively influence user satisfaction."

3. Methods

3.1 Research Design and Instrument

This research constitutes a quantitative study designed to empirically test the relationships between variables in the developed model. Data collection was conducted through a questionnaire structured based on latent constructs, with a total of ten constructs measured using a number of scale items. Items measuring expectation confirmation and performance perception were adapted from Rahi et al. (2019). Meanwhile, the constructs of trend, problem solving, and customization refer to instruments developed by Kim et al. (2016) and Chung et al. (2020). For the constructs of satisfaction and communication, items were taken from the research of Chung et al. (2020) and Joosten et al. (2016). Meanwhile, items related to visual appeal were sourced from the study of Lee & Pan (2023).

3.2 Sampling strategy and data collecting method

This study used a cross-sectional approach, in which data were collected during a specific period, from July to August 2025. The study subjects were bank customers in Indonesia belonging to Generation Y (Gen Y), selected based on their internet usage habits and interest in digital technology (Adhikaputera, 2022; Ogiemwonyi, 2022). The employed sampling technique was purposive sampling, with criteria specifying respondents who had a bank account and are knowledgeable about AI technology, use AI features such as chatbots, biometric-based mobile banking (e.g., fingerprint scanners or facial recognition), and have previously opened a new account digitally.

Considering that the exact population of Generation Y bank customers using AI-enabled digital banking services in Indonesia is unknown, sample adequacy was determined based on the statistical requirements for Partial Least Squares-Structural Equation Modeling (PLS-SEM). The proposed structural model includes seven predictors of the endogenous construct (Satisfaction towards AI Banking). According to J. Hair & Alamer (2022), the minimum sample size based on the 10-times rule is 70 observations. Furthermore, an a priori power analysis using G*Power, assuming a medium effect size ($f^2 = 0.15$), a significance level of 0.05, a statistical power of 0.80, and seven predictors, indicated that a minimum of approximately 103 respondents was required. Therefore, the final sample of 124 valid responses was considered sufficient to ensure adequate statistical power for PLS-SEM.

3.3 Data Analysis

This study used WarpPLS 8 for measurement and analysis with the partial least squares approach. Initially, reliability and validity tests ensured the instrument was sound. Next, the structural model and path coefficients were analyzed to assess variable relationships. These stages verified construct feasibility and tested relationships between constructs (J. Hair & Alamer, 2022).

4. Results

4.1 Respondent Characteristics

Table 1 presents information concerning the gender of the respondents. The study's respondents were predominantly female, as seen by their responses. The mean age of the responders is between 30-39 years. The respondents predominantly possess bachelor's degrees (70.97%), and their occupations are primarily comprised of non-employees (32.26%).

TABLE 1

CHARACTERISTICS OF RESPONDENTS

Demographic variables	Frequency	(%)
Sex		
Male	42	33.87
Female	82	66.12
Age		
20-29	40	32.25
30-39	67	54.03
40-49	17	13.71
Education Level		
High School	2	2
Diploma	15	12
Bachelor	88	70.97
Postgraduate	19	15.33
Occupation		
Government Employee	14	11.29
Lecturer/Teacher	28	22.58
Private Employee	30	24.19
Entrepreneurship	12	9.67
Non-Employee	40	32.26
Total	**124**	**100**

4.2 Measurement Model Analysis

An assessment of the measurement model was conducted to determine the extent to which the indicators used could empirically represent the constructs. The reliability of the indicators was evaluated by examining factor loading values, which indicate the strength of the relationship between each indicator and the latent construct being measured. The evaluation results showed that all items had loading values above 0.60, which is considered the minimum limit recommended in various previous studies. This finding indicates that all indicators make a significant contribution to their respective constructs and have adequate content validity (Hair et al., 2016).

To assess the overall construct reliability, two statistical methods were used: Cronbach's alpha and composite reliability (CR). These two indicators are used to measure the extent to which indicators within a construct demonstrate internal consistency. The research revealed that both Cronbach's alpha and CR scores exceeded the 0.70 threshold., indicating that the construct in this study has a strong level of reliability and is suitable for further analysis (J. F. Hair et al., 2019).

In addition to reliability, construct validity is also a significant concern. Convergent validity was evaluated by the Average Variance Extracted (AVE) value, which represents the proportion of variance accounted for by the construct relative to the variance attributed to measurement error. The AVE values obtained for all constructs were above the threshold of 0.50, showing that most of the indicator variance can be explained by the intended construct (Cheung et al., 2024). This finding strengthens the belief that the constructs used truly represent the theoretical concepts being measured.

Furthermore, to test whether the different constructs in this model are truly discriminatory or conceptually separate, a discriminant validity test was conducted. This test uses a cross-loading approach, which compares the factor load of each item on its construct with the factor load on other constructs. If an item has a higher loading value on the target construct compared to other constructs, then its discriminant validity is likely good. The results of this test indicate that all items meet these criteria, with the highest loading values always being on the intended construct, thus supporting the theoretical and empirical separation of constructs. All empirical evidence supporting the validity and reliability of the construct is presented in detail in Table 2.

TABLE 2

VALIDITY AND RELIABILITY TEST

Variable	Item	Outer loading	AVE	CA	CR
Expectation Confirmation	ECO1	0.816	0.773	0.900	0.931
	ECO2	0.927			
	ECO3	0.809			
	ECO4	0.956			
Perceived Performance	PPR1	0.762	0.628	0.801	0.871
	PPR2	0.782			
	PPR3	0.864			
	PPR4	0.757			
Trendiness	TRE1	0.875	0.766	0.695	0.868
	TRE2	0.875			
Visual Attractiveness	VAT1	0.868	0.807	0.879	0.926
	VAT2	0.948			
	VAT3	0.876			
Problem Solving	PRS1	0.804	0.726	0.808	0.868
	PRS2	0.809			
	PRS3	0.937			
Customization	CUS1	0.742	0.675	0.838	0.892
	CUS2	0.844			
	CUS3	0.876			
	CUS4	0.818			
Communication Quality	CQU1	0.833	0.655	0.730	0.849
	CQU2	0.903			
	CQU3	0.676			
Satisfaction towards AI Banking	SAT1	0.898	0.790	0.867	0.918
	SAT2	0.878			
	SAT3	0.890			

Based on the results at this stage, the measurement model has shown good quality. This means that the indicators used are theoretically relevant and supported by data. This finding provides an important foothold for proceeding to the next stage, namely, analyzing and testing the structural model to determine whether the relationships between the variables that have been formulated influence each other as expected.

4.3 Structural Model Analysis

Table 3 displays the R^2 and adjusted R^2 values for the three dependent variables in the model, namely perception of performance and satisfaction with AI Banking services. Based on the results obtained, the R^2 for the perception of performance reached 50.4%, indicating that the expectation confirmation variable explains 50.4% of the variation in performance perception. Meanwhile, the satisfaction with AI Banking has an R^2 value of 88.8%, indicating that the variables, expectation confirmation, perceived performance, trendiness, visual attractiveness problem solving, customization, and communication quality collectively explain 88.8% of the variation in user satisfaction levels. The structural model is visualized in Figure 3.

TABLE 3

R-SQUARED AND ADJUSTED R-SQUARE COEFFICIENTS

	R square	Adjusted R-square	Level
Perceived Performance	0.504	0.500	Moderate
Satisfaction towards AI Banking	0.888	0.882	Moderate-High

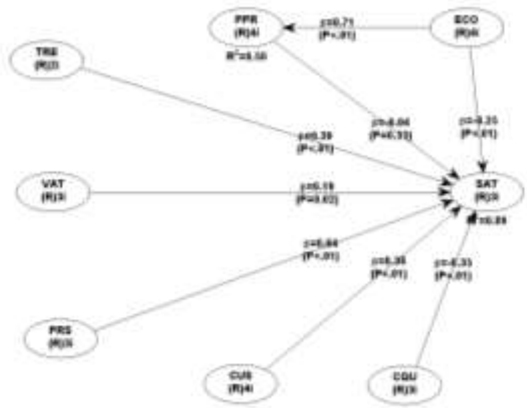

Figure 3. Structural Model Testing

4.4 Hypotheses Testing Analysis

Results of the hypotheses analysis are show in Table 4.

TABLE 4

HYPOTHESES TESTING

	Path	Path Coefficient	P-Values	Decisions
H1	ECO ➔SAT	-0.25	<0.01	Rejected
H2	ECO ➔PPR	0.71	<0.01	Accepted
H3	PPR ➔ SAT	-0.04	0.33	Rejected
H4	TRE ➔ SAT	0.39	<0.01	Accepted
H5	VAT ➔ SAT	0.19	0.02	Accepted
H6	PRS ➔ SAT	0.64	<0.01	Accepted
H7	CUS ➔ SAT	0.36	<0.01	Accepted
H8	CQU ➔ SAT	-0.35	<0.01	Rejected

The statistical results indicate that expectation confirmation has a significant negative impact on user satisfaction with AI-based banking services. This is reflected in the path coefficient value β of -0.25 and $p < 0.01$, so that the first hypothesis (H1) cannot be accepted. Meanwhile, expectation confirmation is proven to have a positive effect on perceived performance, supported by a value of $\beta = 0.71$ and $p < 0.01$, so that the second hypothesis (H2) is accepted. However, perceived performance actually shows a negative effect on user satisfaction with AI Banking, with a value of $\beta = -0.04$ and $p = 0.33$, which means that the third hypothesis (H3) is not supported.

In relation to artificial intelligence features, the results of the study indicate that the variables of trendiness, visual attractiveness, problem solving, and customization contribute positively and significantly to satisfaction with AI Banking services. This is reflected in the respective path coefficient values: $\beta = 0.39$; $\beta = 0.19$; $\beta = 0.64$; and $\beta = 0.36$ and $p < 0.05$, so that hypotheses H4, H5, H6, and H7 are declared accepted. However, the effect of communication quality on user satisfaction with AI Banking is not empirically supported. The findings show a negative path coefficient of $\beta = -0.35$ and $p < 0.01$, so that hypothesis H8 is rejected.

5. Discussion

Empirical research results indicate that expectation confirmation has no positive (negative) effect on user satisfaction; however, it has a positive and significant impact on perceived performance. Empirical results also indicate that perceived performance does not have a positive effect on user satisfaction. Expectation confirmation refers to users' expectations for AI-based banking services (Mi Alnaser et al., 2023). However, in this context, Generation Y customers may have very high expectations for AI-based banking services, such as chatbots, that are expected to provide emotional and personalized experiences. Therefore, when AI services operate only according to their expectations, this condition is seen as a minimum standard rather than added value capable of creating satisfaction. This finding is in line with the Expectation-Disconfirmation Theory proposed by Oliver (1980), which states that satisfaction is a function of disconfirmation, where higher satisfaction occurs when service performance exceeds expectations (positive disconfirmation), rather than simply meeting them. For Generation Y, AI services that only meet initial expectations tend to be considered something ordinary and therefore insufficient to increase satisfaction, although they can still improve perceptions of service performance. This means that confirmation of expectations alone is not enough to increase user satisfaction (Schiebler et al., 2025). Meanwhile, regarding perceived performance, confirmation of expectations makes users feel that AI banking services function as expected, thereby significantly increasing their perception of performance. However, to increase subjective and emotional satisfaction, more than just confirmation of expectations and perceived performance is needed, such as trust and the overall user experience (Toli & Bharata, 2024).

Furthermore, research related to AI features shows that AI features consisting of trendiness, visual attractiveness, problem-solving, and customization have been shown to have a significant and positive effect on user satisfaction. This finding aligns with the research conducted by Mi Alnaser et al. (2023). Trendiness makes AI services feel modern and relevant to the needs of today's users, thereby increasing user appeal and satisfaction (Bhandari et al., 2019; Ho et al., 2023). Visual attractiveness enhances the user experience aesthetically, making interactions with the application more enjoyable and understandable, which contributes to satisfaction (Bhandari et al., 2019; Lee & Pan, 2023). Problem-solving provides real added value for users by facilitating the resolution of financial needs quickly and efficiently, thereby increasing satisfaction (Chung et al., 2020; Kim et al., 2016). Customization allows AI services to tailor features and recommendations to user preferences and conditions, making the experience more personalized and relevant, which significantly increases user satisfaction (Bulawa & Hartwig, 2023).

However, the research results failed to prove that AI features, namely communication quality, have a positive impact on user satisfaction. This is because although AI for instance chatbots and virtual assistants may be providing fast and automatic responses, the quality of empathetic, personal, and in-depth communication is often still lacking compared to human interaction. This makes AI communication less effective in meeting the emotional and psychological needs of customers, and therefore does not significantly increase user satisfaction. Thus, although effective communication is a crucial aspect of AI, in the context of AI-based banking, mechanical and less personal communication is not enough to significantly increase user satisfaction. The development of more empathetic and adaptive AI communication is needed to contribute positively to user satisfaction (Ho et al., 2023).

6. Conclusions

The banking industry has evolved to keep pace with digital developments by adopting technologies, including artificial intelligence. This study aims to assess banking user satisfaction of AI-based digital banking. This research was conducted among generation Y users of banking services in Indonesia.

The research findings highlight that meeting expectations and perceptions of system performance are not sufficient to build user satisfaction in the context of AI-based banking services. This confirms that the cognitive dimension emphasized in the TAM model needs to be complemented by affective aspects, such as emotional experiences and interpersonal interactions, to explain user satisfaction more comprehensively (Zahidi et al., 2024)

Conversely, AI features consist trendiness, visual attractiveness, problem-solving capabilities, and customization have been shown to significantly impact user satisfaction. These features reflect the added value of aesthetics, relevance, efficiency, and AI's ability to provide more personalized and contextual services. However, communication quality, one of the AI features, did not significantly impact user satisfaction. This highlights the limitations of AI communication, which often appears mechanical and lacks empathy, thereby failing to meet customers' emotional needs and replicate human interaction.

This study builds on the expectation confirmation theory (ECT) by providing new insights, specifically, how users' expectations and the features of AI technology influence their overall satisfaction. On a practical level, the findings offer valuable input for developers of AI in the banking sector. It is not just about making systems faster and more accurate; it is also about creating a user experience that feels emotionally satisfying and builds a sense of connection with the technology.

Although this study offers valuable insights, it also has some limitations that create opportunities for further research. One key limitation is the absence of affective variables, such as trust, emotional engagement, and empathy, which are likely to play a significant role in shaping user satisfaction. To get a deeper knowledge of how users relate to AI, future studies are encouraged to incorporate these emotional factors, such as perceived empathy and emotional satisfaction, into the model when exploring human-AI interactions.

Furthermore, this study mainly draws insights from younger users, who are indeed the most active in using mobile apps. However, focusing on this specific group may limit the applicability of the findings to the wider demographic. Future research could involve a larger and more diverse group of users from various regions and age groups to attain a more comprehensive understanding of sentiments around AI-based financial services.

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