Digital Business 5 (2025) 100103

Contents lists available at ScienceDirect

Digital Business

journal homepage: www.elsevier.com/locate/digbus

An empirical study on the use of artificial intelligence in the banking sector of Indonesia by extending the TAM model and the moderating effect of perceived trust

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ARTICLE INFO

Keywords:
Technology acceptance model
Awareness
Subjective norm
Perceived risk and trust
Artificial intelligence

ABSTRACT

Artificial intelligence technology is increasingly becoming integral in business, and banks need to implement this technology on a large scale for competitiveness. However, studies on artificial intelligence in the banking sector are limited, and customers are concerned about its implementation. Therefore, this study aims to measure the intention to continue adopting artificial intelligence in Indonesia's banking sector. This study proposed nineteen hypotheses and used a technology acceptance model framework with the awareness of artificial intelligence, subjective norms, perceived risk, and perceived trust as extensions. The researchers surveyed 388 bank customers who have interacted with artificial intelligence. The survey results extended the technology acceptance model framework by accepting all the hypotheses. This study contributes to the banking industry of developing countries by generating artificial intelligence technology with a high level of security.

1. Introduction

The success of companies in winning the competition in Industry 4.0 is determined by their ability to adopt technological innovations despite the challenges and implementation methods. Based on SDG 9 (building resilient infrastructure, promoting inclusive and sustainable industrialization, and fostering innovation), companies need to adjust their vision and mission toward a digital strategy to face various challenges in the market (Zangiacomi et al., 2020). Additionally, all company departments must commit to adopting new technologies. Artificial intelligence (AI) is a crucial component in defining Industry 4.0 (Jan et al., 2023) and implementing technological innovations.

Using AI to manage knowledge without human intervention significantly impacts the banking sector (Atwal & Bryson, 2021). The McKinsey Global Institute report explains that using AI and machine learning in the banking sector can improve the ability to make decisions, customize services, and enhance risk management (Babel et al., 2019). Globally, the Statista, 2023 report reveals that the AI adoption rate in the financial sector continues to grow from 2022 to 2025. In 2022, 46 % of global companies have adopted AI, and by 2025, 43 % will have included AI in their services (Thormundsson, 2023). This report allowed the financial sector to continue adopting and investing in AI to improve services. Tarafdar et al. (2020) emphasize that AI has led to better sales and guided the development of effective customer relationship management systems. Furthermore, a McKinsey report uncovered that approximately 60 % of banks worldwide have used AI, such as virtual assistants, fraud detection tools, and real-time risk monitoring means (Biswas et al., 2020).

In Indonesia, an International Business Machines Corporation study reported that with AI implementation in the financial services and manufacturing sectors, 62 % of companies have invested in creating AI pilot programs, and 23 % remain in the investment stage and have adopted AI capabilities to interact with a company's business functions (Vedhitya, 2024). The AI adoption rate has reached 60 % globally and in Indonesia; nonetheless, a report by the U.S. Department of the Treasury (2024) revealed that financial institutions will slowly adopt AI technologies owing to risk management considerations (Treasury, 2024).

The main challenge for Indonesia's banking sector in implementing

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https://doi.org/10.1016/j.digbus.2024.100103
Received 4 August 2024; Received in revised form 26 December 2024; Accepted 26 December 2024
Available online 29 December 2024

AI is increasing the capacity, reliability, and security of transactions. The growth in digital transactions reinforces this condition. However, the level of cybercrime and digital fraud is also on the increase (Despotović et al., 2023; Fares et al., 2023). The banking industry can improve the security of digital transactions via AI algorithms (Rahman et al., 2023) and enhance the effectiveness and efficiency of business transactions (Liu et al., 2024). AI has substantial benefits; however, customers face certain risks and disadvantages when adopting it. Such risks include the loss of privacy and personal data (Murdoch, 2021) and the inability to understand AI. However, from a bank's perspective, AI can increase revenue through service personalization (to customers and employees), alleviate costs due to automation, and reduce error rates (Biswas et al., 2020). For example, a digital bank in Indonesia (Bank Jago) has implemented AI through Google Cloud's Vertex AI platform for various business processes, including customer onboarding and call center prototyping. Meanwhile, several other banks in Indonesia use chatbot features, biometric identity verification technology, and mobile banking, which are interaction-based algorithms and AI.

With the increasing use of AI in the banking sector and the growing focus on customer-centric services, more research is urgently required on customer behavior in Indonesia regarding AI adoption. Previous studies have explored various aspects of AI use, such as continuance usage intention (Lv et al., 2022), usage behavior (Gansser & Reich, 2021), satisfaction, trust, and experience (Uzir et al., 2021). Continued usage behavior is often studied in terms of the acceptance and use of certain technologies (Khayer & Bao, 2020). Table 1 outlines the existing research gaps, underscoring the need for further studies on customer behavior in adopting AI in the banking sector. Understanding customer perceptions and readiness is essential to successfully implement AI in the banking sector. (See Fig. 1.)

The research gaps in various technology adoptions identified in Table 1 and the lack of AI adoption studies in the banking sector, especially in Indonesia, motivated the author to evaluate the readiness and sustainability of AI use and Industry 4.0, using the Technology Acceptance Model (TAM) framework (Davis, 1989). TAM assessed the acceptance and use of technology via two primary constructs: perceived usefulness and perceived ease of use. However, this model is open to the contribution of external factors to produce a more comprehensive coverage. Therefore, this study explored AI awareness, subjective norms, perceived risk, and perceived trust as TAM extensions (Davis, 1989). These factors are necessary for customers in the early stages of technology adoption. For example, realizing that technology helps to support activities (Singh & Sinha, 2020), the presence of customers who adopt AI (Rahman et al., 2023), the impact of the risks faced, and the level of trust in AI (Hasan et al., 2021). Implementing AI is relatively new in Indonesia. Thus, studying customer perceptions when adopting AI in its early stages and customer readiness to continue using AI is necessary. The empirical evidence from this study can help practitioners and the Indonesian government develop strategies and policies for using AI in the banking sector.

Millennials, or the digital generation, were born between 1981 and 1996. They grew up amidst the rapid development of information and communication technologies, such as the Internet, mobile phones, and social media. This generation is familiar with technology and is often an early adopter of digital innovations. Concerning the peak demographic bonus predicted to occur in Indonesia in 2035, the millennial generation is expected to have a higher income level than other generations (Suhartanto et al., 2022). By 2025, approximately 70 million millennials will become bank customers, strengthening their dominance in the financial sector. Digital banks in Indonesia have increasingly attracted the attention of millennials because they offer various banking services that are convenient, fast, and easy to use for their all-digital lifestyles (Statista, 2023). Against this background, this study focuses on the behavior of Indonesian millennials toward AI use in banking services.

This paper comprises six sections. The first section reviews the relevant phenomena and research gaps as the basis for this study. The second section explains the literature review and provides the basis for the framework and hypotheses. The third section outlines the research strategy and summarizes the methodology. The fourth section presents the research findings. The fifth section discusses the findings theoretically and practically. The last section provides the conclusions, research limitations, and directions for future research.

2. Research background

2.1. AI Adoption in the Indonesian banking sector

AI is designed like a human with the knowledge and ability to learn, feel, think, and act for users to obtain good analytical insights (Vlačić et al., 2021). AI can operate automatically in the banking sector without human assistance. This is due to the support of machine learning in finding data patterns, which helps make the right decisions (Al-Dosari et al., 2024). In addition, AI encourages banks to widen access to multichannel customers, provides insights into customer preferences, and personalizes services according to customer needs (Lee & Lee, 2020). In addition, banking applications on smartphones also provide customers with easy access to banking services.

Indonesian banks adopted AI to improve their operation. For example, machine learning can analyze transactions in graph visualizations to assist data-driven decision-making and abnormal customer behavior detection to minimize fraud (Afriyie et al., 2023), and machine learning technology can detect patterns of fraud and cyber-attacks. Related to the purpose of this study, AI technologies used by customers include face scanning for transactions, voice commands, virtual assistants in mobile banking, chatbots for information services, fingerprints, and biometrics for authentication and authorization processes. AI adoption can streamline customer transactions; nonetheless, several obstacles hinder its use. We conducted in-depth interviews with Indonesian banking practitioners to understand these barriers. From the interviews, we identified four major factors preventing customers from adopting AI in Indonesia, highlighting the importance of this research.

First, regarding risk perception and trust, customers must understand AI. "*Many customers in Indonesia need to understand how AI works in banking services, which may lead to distrust or hesitation when using AI-based services. Risks that customers in Indonesia may face include bias in algorithms, deepfakes, and automated decisions made by AI*" (interview, September 2024). Second, there are concerns regarding the privacy and security of customer data in Indonesia. This relates to the level of awareness and understanding of AI. "*While AI can improve efficiency and personalization of services, customers feel insecure about how their data is used and stored. In addition, there are concerns that AI may open loopholes for data leakage or misuse of personal information*" (interview, September 2024). Regarding subjective norms, "*many people around the customer (e.g., friends, family, or colleagues) are concerned about data privacy and security. The concern is more substantial, and they are reluctant to use AI-based services*" (interview, September 2024). The third factor is the digital divide. "*In Indonesia, the digital divide is still a significant problem. Fast and reliable internet access is still restricted, and the low level of digital literacy makes AI-based service technology less attractive to customers in Indonesia*" (interview, September 2024). The digital divide can affect the ability to use technology and customers' views on its usefulness. In addition, with limited internet access, customers experience challenges using AI-based applications or services. Without good digital skills, customers cannot maximize the functions and features offered by AI, resulting in a low perception of its usefulness. Lastly, "*there needs to be more mature policies and regulations. Regulations and policies related to AI use in Indonesia's banking sector may need to be fully mature. This regulatory uncertainty may hinder banks from adopting AI technology widely*" (interview, September 2024). Therefore, banks must ensure certainty regarding AI regulations.

Table 1
Research Gap of Technology Adoption in The Last Four Years.

Authors	Hypothesis	Technology Adoption	Finding	
			Accepted	Rejected
Damerji and Salimi (2021)	Perceived ease of use→Perceived usefulness	AI in Auditing	Yes	–
Liu et al. (2022)	Perceived ease of use→Behavioral Intention	Smart hospitality	–	Yes
	Perceived usefulness→Behavioral Intention		Yes	–
Liu and Luo (2021)	Perceived ease of use→Perceived usefulness	Youtube	–	Yes
	Perceived ease of use→Behavioral Intention		Yes	–
	Perceived usefulness→Behavioral Intention		Yes	–
Rahman et al. (2023)	Perceived ease of use→Attitude toward AI	AI in banking	–	Yes
	Perceived usefulness→Attitude toward AI		Yes	–
	Perceived ease of use→Behavioral Intention		–	Yes
	Attitude toward AI→Behavioral Intention		Yes	–
	Subjective norms→Behavioral Intention		Yes	–
	Awareness of AI→Behavioral Intention		–	Yes
	Perceived risk→Behavioral Intention		Yes	–
Abdullah and Almaqtari (2024)	Perceived ease of use→Perceived usefulness	AI in Auditing	–	Yes
	Perceived ease of use→Behavioral Intention		Yes	–
Kashive et al. (2021)	Perceived ease of use→Attitude toward AI	AI in e-learning	Yes	–
	Perceived usefulness→Attitude toward AI		–	Yes
	Attitude toward AI→Behavioral Intention		–	Yes
Wang, Wang, et al. (2021)	Perceived usefulness→Attitude toward AI	AI in higher education	–	Yes
	Perceived ease of use→Perceived usefulness		Yes	–
	Perceived ease of use→Attitude toward AI		Yes	–
	Perceived usefulness→Behavioral Intention		Yes	–
	Attitude toward AI→Behavioral Intention		Yes	
	Perceived ease of use→Behavioral Intention		–	Yes
Roy et al. (2022)	Perceived ease of use→Perceived usefulness	AI-Based Robots	Yes	–
	Perceived usefulness→Attitude toward AI		Yes	–
	Perceived ease of use→Attitude toward AI		Yes	–
	Subjective norms→ Behavioral Intention		Yes	–
	Attitude toward AI→Behavioral Intention		Yes	–
Suzianti and Paramadini (2021)	Perceived usefulness→Continuance Intention	*E*-Learning	–	Yes
Singh, Sahni, and Kovid (2020)	Perceived ease of use→Perceived usefulness	Fintech	Yes	–
	Perceived ease of use → Behavioral Intention		Yes	–
	Subjective norms→ Behavioral Intention		–	Yes
Cho and Lee (2020)	Perceived ease of use→Continuance intention	Smart device for physical disabilities	–	Yes
	Perceived usefulness→Continuance intention		Yes	–
Singh and Sinha (2020)	Awareness of AI→Perceived usefulness	Mobile wallet	Yes	–
	Perceived usefulness→Behavioral intention		Yes	–
Ashfaq et al. (2020)	Perceived usefulness→Continuance intention	AI in service agents	Yes	–
	Perceived ease of use→Continuance intention		Yes	–
Liébana-Cabanillas et al. (2021)	Perceived risk→Continuance intention	NFC mobile payments	Yes	–
	Subjective norms→Continuance intention		Yes	–
	Perceived usefulness→Continuance intention		Yes	–
Rahi et al. (2021)	Attitude toward AI→Continuance intention	Internet banking	Yes	–
	Perceived usefulness→Continuance intention		Yes	–
	Perceived usefulness→Attitude toward AI		–	Yes
	Perceived ease of use→Attitude toward AI		Yes	–
	Perceived ease of use→Perceived usefulness		Yes	–
Shahzad et al. (2024)	Awareness of AI→Behavioral Intention	Cryptocurrency	Yes	–
Thomas-Francois and Somogyi (2023)	Perceived risk→Behavioral Intention	Smart grocery shopping	Yes	–
	Perceived ease of use→Behavioral intention		–	Yes
Saif et al. (2024)	Perceived ease of use→Behavioral intention	AI in e-learning	–	Yes
	Perceived usefulness→ Attitude toward AI		–	Yes
Jo and Bang (2023)	Perceived ease of use→Continuance intention	Enterprise Resource Planning	–	Yes
Richter et al. (2023)	Perceived usefulness→Continuance intention	*E*-book	Yes	–
	Perceived ease of use→Behavioral intention		–	Yes
	Perceived usefulness→Behavioral intention		Yes	–
Jnr and Petersen (2023)	Perceived ease of use→Behavioral intention	Enterprise architecture in smart cities	Yes	–
	Perceived usefulness→Behavioral intention		–	Yes
	Perceived ease of use→Perceived usefulness		Yes	–
Foroughi et al. (2024)	Perceived usefulness→Continuance intention	Food delivery apps	–	Yes
	Perceived ease of use→Perceived usefulness		Yes	–
	Perceived usefulness→Attitude toward AI		Yes	–
	Perceived ease of use→Attitude toward AI		–	Yes
	Attitude toward AI→Continuance intention		Yes	–
Goel and Haldar (2020)	Perceived ease of use→Attitude toward AI	Ride-hailing apps	–	Yes
Alsadoun et al. (2023)	Perceived risk→Behavioral Intention	Online Pharmacy	–	Yes
	Awareness of AI→Behavioral Intention		Yes	–
Kaur and Arora (2022)	Perceived risk→Behavioral Intention	Online banking	Yes	–
Nguyen et al. (2024)	Awareness of AI→Continuance intention	*E*-payment	Yes	–
Singh, Sinha, and Liébana-Cabanillas (2020)	Subjective norms→Continuance intention	Mobile wallet	Yes	
	Perceived risk→Behavioral Intention		–	Yes
	Perceived ease of use→Behavioral Intention		Yes	–
	Perceived usefulness→Behavioral Intention		Yes	–

(*continued on next page*)

Table 1 (*continued*)

Authors	Hypothesis	Technology Adoption	Finding	
			Accepted	Rejected
Chatterjee et al. (2021)	Behavioral Intention→Continuance intention	AI-integrated CRM	Yes	–
Nguyen and Dao (2024)	Behavioral Intention→Continuance intention	Mobile banking	Yes	
	Subjective norms→Continuance intention		–	Yes
	Perceived usefulness→Behavioral Intention		Yes	–
	Perceived usefulness→Behavioral Intention		Yes	
	Subjective norms→Behavioral Intention		Yes	–

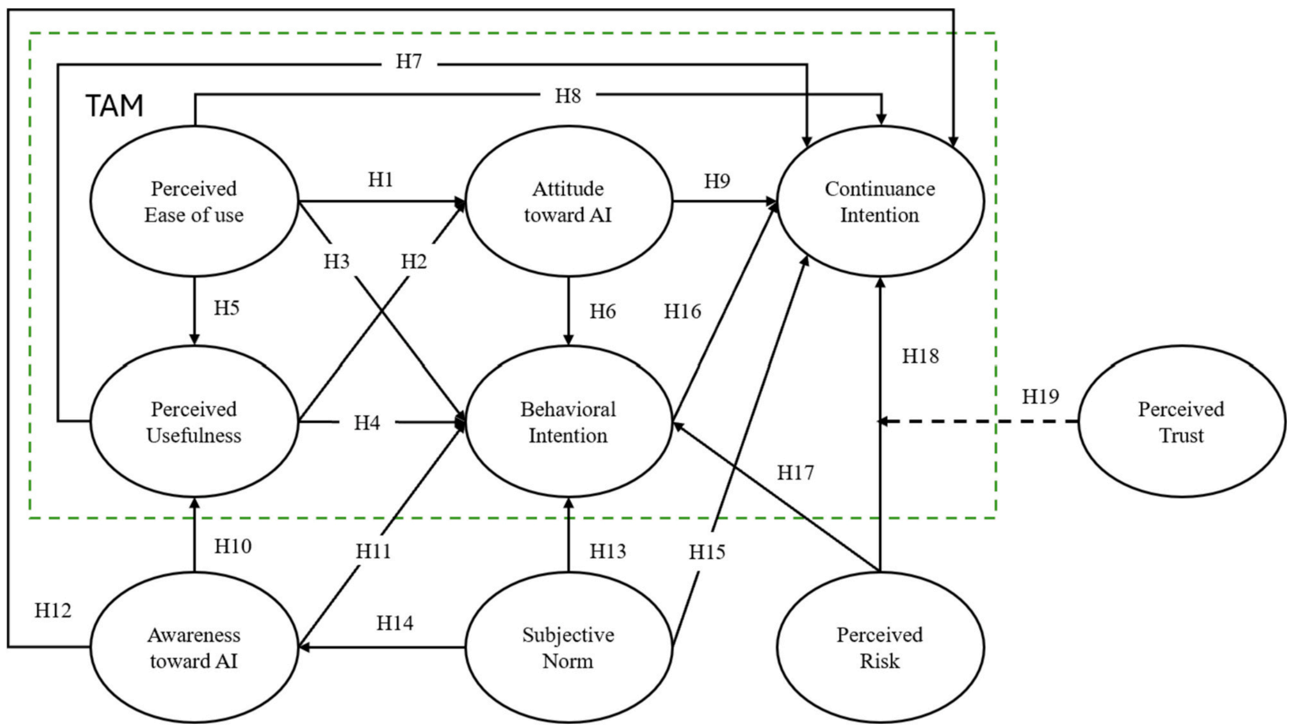

Fig. 1. Model Framework.

2.2. *Empirical study on AI adoption in developing countries*

This study examines AI acceptance in the banking sector of Indonesia, which is a developing country in the early adoption stages. Table 2 reveals that scholars have studied AI in several developing countries and observed that AI contributes considerably to the banking sector. For example, in Vietnam, metaverse acceptance in banking services faced challenges, whereas AI improved service quality, customer satisfaction, and credit risk management in Jordan and Pakistan. Additionally, a study in Malaysia focused on the regulatory and data security challenges in AI adoption, whereas banking chatbots emphasized the importance of security and responsiveness in Nigeria. Therefore, AI application requires more comprehensive studies from scholars in developing countries, especially from a consumer perspective, to provide insights into the banking sector and improve customer service and banking performance.

3. Theoretical foundation and hypothesis development

3.1. *Continuance intention*

Technology continuance theory was first developed by Liao et al. (2009) to assess whether users intend to continue or stop using a technology. This theory is formed by integrating three information system models–the TAM, expectation confirmation theory (ECT), and cognitive model–to predict the long-term usage behavior of innovative technologies (Liao et al., 2009). Furthermore, the ECT model provides an initial description of post-purchase customer behavior (Oliver, 1980). Referring to the conceptual ECT, the expectation-confirmation model was formed for the continued use of information technology (Bhattacherjee, 2001). Researchers often use the TAM and Theory of Planned Behavior to investigate the factors that encourage customers to accept certain technologies in the early stages of implementation. However, examining the sustainable use of technology is also necessary (Bergmann et al., 2023). Bergmann et al. (2023) explained that customer decisions are identical to the decision to continue using a particular technology. This is because both decisions involve initial decisions (adoption and experience in using technology), leading to early decision-making. In this study, the intention to continue using AI was the customers' willingness to use AI technology in the future. A technology will not succeed if users do not adopt or benefit from it (Bhattacherjee & Lin, 2015).

3.2. *Technology acceptance model*

Researchers have widely used the TAM to evaluate customer technology perceptions. Davis (1989) developed TAM as a framework to explore customer perceptions when adopting new technology. The resulting constructs are perceived usefulness and ease of use, which become the central assessments for customers to form attitudes toward technology. Behavioral intention determines the adoption and use of technology. Behavioral intention is determined by users' attitudes

Table 2
Review of Empirical Studies on the Use of AI for the Banking Sector.

Authors and Years	Purpose	Data	Result
Nguyen et al. (2023)	The study proposes the acceptance and use of the metaverse technology model, which consists of metaverse performance expectations, metaverse facilitating conditions, metaverse effort expectations, and metaverse social influence to determine the adoption of metaverse banking services.	Survey: 491 bank customers in Vietnam	The results show that metaverse financial resources and behavioral intentions do not support the research hypothesis.
Al-Araj et al. (2022)	Importance of AI in services provided by Jordanian banks for customer satisfaction	Survey: 270 customers in Jordan's banking sector.	AI implementation is statistically relevant to service quality and customer satisfaction.
Mi Alnaser et al. (2023)	Develop and integrate an expectation confirmation model and examine digital banking customer satisfaction and acceptance of AI-enabled digital banking.	Survey: 320 digital banking customers (commercial and Islamic banks in Pakistan).	Customer satisfaction is determined by expectation confirmation, perceived performance, trending, visual appeal, problem-solving, customization, and communication quality, except trending and customization.
Qasaimeh and Jaradeh (2022)	Identifying the impact of expert systems, neural networks, genetic algorithms, and intelligent agents on cyber governance in Jordanian commercial banks.	Survey: 208 Jordanian commercial banks.	Implementing cyber governance in Jordanian commercial banks relies on AI techniques and applications (expert systems, neural networks, genetic algorithms, and intelligent agents).
Mogaji et al. (2021)	Explore how consumers in emerging markets interact and engage with banking chatbots when completing bank transactions.	Interview: 36 Nigerian residents.	This study demonstrates how the UTAUT factors explain consumer interaction with banking chatbots in developing countries. Age and technology experience facilitate chatbot use, while perceived expertise, responsiveness, and security are also crucial. The study focuses on user experiences with conversational interfaces in emerging markets.
Boustani (2022)	The application of AI in the banking sector, its impact on bank employees, and customer behavior when purchasing financial services. The importance of AI for delivering social services in developing countries in West Asia.	Sample: 50 bank employees and 250 customers. Asian developing country.	Customers are more satisfied using AI and receiving automated customer service. AI technology can drive time efficiency. Financial innovation can lead to transformation in the banking profession, eliminating specific jobs and creating new ones. Financial innovation can fulfill soft skill needs in jobs.
Rahman et al. (2023)	Understand the importance and challenges of adopting AI in the banking industry in Malaysia and identify the factors influencing customer intention to adopt AI.	In-depth interviews: officials in the baking industry Survey: 302 Malaysian banking customers.	**Qualitative** AI technology is becoming a fraud detection and risk prevention tool. However, there are no regulations, low data privacy and security levels, and a lack of skills and infrastructure, which are challenges in AI adoption. **Quantitative** Attitude, perceived usefulness, perceived risk, perceived trust, and subjective norms significantly affect AI adoption intention. Perceived ease of use and awareness do not affect the intention to adopt AI. Attitude significantly mediates the relationship between perceived usefulness and the intention to adopt AI.
Almustafa et al. (2023)	Identify AI's transformative potential to improve financial services in commercial banks in Jordan, focusing on credit risk management.	Survey: 143 employees banks in Amman, Jordan.	AI technology provides accurate credit scoring results, precise market risk analysis, better financial forecasting capabilities, robust risk model validation, and more sophisticated creditworthiness evaluation. In addition, AI offers opportunities for personalized customer service solutions, enhancing the experience and guiding customers toward the right financial services.
Mi Alnaser et al. (2023)	Develop and integrate AI-enabled digital banking user expectation, satisfaction, and acceptance confirmation models.	Survey: 251 customers of commercial and Islamic banks in Pakistan.	Digital banking customer satisfaction is determined by expectation confirmation, perceived performance, trending, visual appeal, problem-solving, customization, and communication quality. Communication quality, corporate reputation,

(continued on next page)

Table 2 (*continued*)

Authors and Years	Purpose	Data	Result
			expectation confirmation, perceived performance, problem-solving, trending, and visual appeal significantly affect satisfaction, except for trending and customization.

toward technology and their perceived usefulness. The TAM also recognizes the involvement of external factors that can influence the perceived usefulness and ease of use. These external factors form the basis for researchers to expand the acceptance models of specific technologies. Furthermore, the TAM has been widely used in information systems to explain user intentions to adopt and use new technologies (Al-Adwan et al., 2023).

3.3. Perceived usefulness

The TAM suggests that perceived usefulness influences an individual's intention to adopt a technology. Perceived usefulness is an individual's perception of a technology that can improve their effectiveness on a task (Khlaif et al., 2023). In this study, conceptual perceived usefulness is a statement made by bank customers who believe that using AI will be helpful and improve transaction performance quickly and with minimal effort.

The TAM highlights perceived usefulness as a determinant of attitudes and behavioral intentions. Bank customers perceive the benefits of using AI features to support smooth transactions, thus encouraging them to have a positive attitude toward technology (Rahman et al., 2023). Laksamana et al. (2022) and Alhassan et al. (2020) proved that perceived usefulness can shape and explain customers' attitudes toward mobile payment (Asnakew, 2020). Regarding behavioral intentions when using financial technology, several researchers have revealed that perceived usefulness determines customer behavioral intentions (Singh, Sahni, & Kovid, 2020; Singh & Sinha, 2020). Thus, customers have positive attitudes and behaviors toward technology because they perceive its benefits.

Referring to the continued intention to use technology in the financial and banking sectors, customers who benefit from technology will commit to using it to support transaction activities (Aprilia & Amalia, 2023; Ashfaq et al., 2020; Inan et al., 2023; Nagadeepa et al., 2024; Rahi et al., 2021). This study assumes that AI can benefit customers in the banking sector by supporting every transaction. Therefore, AI contributes to shaping optimistic attitudes and behaviors, as indicated by the customer's willingness to continue using it. From the banks' perspective, operations have become more effective and efficient.

Based on the findings of previous research, this study hypothesized the following:

H2. Perceived usefulness positively influences customer attitudes toward AI.

H4. Perceived usefulness positively influences behavioral intention to use AI.

H7. Perceived usefulness positively influences continuance intention to use AI.

3.4. Perceived ease of use

Perceived ease of use refers to the customer's understanding that technology is easy to operate, impacting the adoption of innovative services or products (Davis, 1989; Martínez-Navalón et al., 2023). Perceived ease of use refers to the extent to which innovations are easy to understand, learn, and use (Masoud & AbuTaqa, 2017). Therefore, customers' responses to technology can lead to their willingness to use or abandon it. Furthermore, when customers are unfamiliar with or worried about technology use, they must make a solid effort to understand it. Concerns about the difficulty of adopting technology can lead to negative attitudes toward it. Conversely, customers who use technology easily generate useful and positive attitudes that lead to behavioral intentions to use it (Malaquias & Hwang, 2019). In this study, perceived ease of use refers to bank customers believing that AI is easy to understand and supports banking transactions.

Studies have revealed that perceived ease of use positively impacts the perceived usefulness of AI in the education sector (Roy et al., 2022; Wang, Liu, & Tu, 2021), Internet banking (Rahi et al., 2021), enterprise architecture (Jnr & Petersen, 2023), and financial auditing (Damerji & Salimi, 2021). Customers' behavioral intentions to adopt Fintech services are influenced by perceived ease of use. For example, Singh, Sahni, and Kovid (2020) explained that Fintech applications are designed for user convenience with clarity of navigation and positively impact intentions to continue using applications.

The ease of technology use can shape customer attitudes and sustainability. Some empirical evidence from previous studies related to AI use in the education sector explains that perceived ease of use positively impacts user attitudes (Kashive et al., 2021; Roy et al., 2022; Wang, Liu, & Tu, 2021). In using Internet banking, Rahi et al. (2021) proved that customer attitudes are determined by perceived ease of use. The same findings can be explained in the context of mobile banking (Asnakew, 2020). Furthermore, when using Fintech services, perceived ease of use positively affects customer behavioral intentions (Singh, Sahni, & Kovid, 2020). A study on AI-based customer service explained that perceived ease of use determines the sustainability of chatbots (Ashfaq et al., 2020). Based on previous research findings, this study assumes that a banking industry that invests in AI-based technology that customers find easy to understand will positively impact the bank's sustainability and generate loyal customers. Therefore, this study hypothesized the following:

H1. Perceived ease of use positively influences attitude toward AI.

H3: Perceived ease of use positively influences behavioral intention to use AI.

H5. Perceived ease of use positively influences the perceived usefulness of using AI.

H8. Perceived ease of use positively influences continuance intention to use AI.

3.5. Attitude toward AI

In the TAM, attitude is an essential mediator in the relationship between perceived usefulness and perceived ease of use with user behavioral intentions. Conceptually, when customers have a positive attitude toward technology, their intention to use it increases (Davis, 1989). In this study, bank customers' attitudes are in the form of evaluative statements or the result of their feelings toward using AI. Positive evaluation results from bank customers using AI will lead to the formation of behavioral intentions and commitment to continue using AI. Rahman et al. (2023) explained that in the banking sector, customers who adopt AI in the early stages generate positive attitudes that affect behavioral intentions to use AI.

Similarly, when using AI in education, students have a positive attitude toward using AI-based robots during class activities (Roy et al., 2022). Furthermore, customers positively evaluate the use of Internet banking; hence, they decide to use the technology continuously in every financial transaction (Rahi et al., 2021). Similar results are also described in the context of mobile payments (Mobarak et al., 2024; Srivastava & Singh, 2023). Based on the results of empirical studies, this study assumes that implementing AI in the banking sector will result in positive changes in customer attitudes. These attitudes drive behavioral changes that lead to the willingness to continue using AI. Therefore, this study hypothesized the following:

H6: Attitude toward AI positively influences behavioral intention to use AI.

H9: Attitude toward AI positively influences continuance intention to use AI.

3.6. Behavioral intention

The TAM's theoretical framework of behavioral intention is the output of customer attitudes after using technology. Customer attitude can lead to acceptance or rejection during the early stages of technology use (Bergmann et al., 2023). In this study, behavioral intention is the initial action taken by bank customers to adopt AI, which can determine the direction of continued use. Previous researchers have conflated the relationship between behavioral intention and sustainability of technology use in a limited manner. For example, Chatterjee et al. (2021) studied AI adoption by integrating it with customer relationship management systems and explained that behavioral intentions can influence employees to continue using AI-based customer relationship management systems. Lin (2017) explained that behavioral intention affects continuance intention in using online carbon footprint calculators. Furthermore, Nguyen and Dao (2024) observed that behavioral intention considerably affects mobile banking continuance intention. Therefore, this study hypothesized the following:

H16: Behavioral intention positively influences continuance intention to use AI.

3.7. Awareness of AI

Awareness is the output of the communication strategy that companies use to make customers aware of the benefits and uses of specific technologies (Singh & Sinha, 2020). This study interprets customer awareness as a motivating factor for companies to encourage customers to use AI during banking. The lack of customer awareness is an obstacle for companies in implementing the designed technology (Mutahar et al., 2018). Companies believe that awareness of technological innovation can influence customer behavioral intentions (Flavián et al., 2022). Thus, when customers are aware of technology and have an initial knowledge of it, they are willing to adopt innovations. (Kasim & Wickens, 2020). In addition, the fear of losing personal data and data misuse by third parties encourages customers to minimize their interaction with technology, thus affecting the acceptance of the technology.

Some empirical evidence sheds light on the relationship between customer awareness and the perceived usefulness, behavioral intention, and continuance-intention of technology. For example, Singh and Sinha (2020) observed a strong relationship between customer awareness and perceived usefulness. This implies that customer perceptions of the usefulness of technology depend on their level of awareness. Furthermore, studies explain that customer technology awareness can help activities that lead to customer behavioral intentions (Alsadoun et al., 2023; Jamshidi & Kazemi, 2020; Shahzad et al., 2024). Kumari and Biswas (2024) also explained that customer awareness can shape attitudes and strengthen the intention to continue using technology. There is a lack of empirical studies on customer awareness in the TAM. Therefore, this study hypothesized the following:

H10: Awareness of AI positively affects perceived usefulness.

H11: Awareness of AI positively influences behavioral intention to use AI.

H12: Awareness of AI positively influences continuance intention to use AI.

3.8. Subjective norm

According to the Theory of Planned Behavior framework, Fishbein and Ajzen (1977) defined subjective norms as "the belief that an important person or group of people will approve and support a particular behavior." In addition, social influence and subjective norms are the same, namely the influence and opinions of others (Taylor & Todd, 1995). In this study, subjective norms are a form of encouragement and opinion from others around customers who suggest adopting AI in banking. This view aligns with those of previous researchers who have adopted AI and explains that other people positively impact their behavioral intentions to use AI (Rahman et al., 2023). Mer and Virdi (2021) reported the same results for e-banking use, and Hamilton et al. (2021) for e-health services. In studies on bank chatbot services, Nagadeepa et al. (2024) observed a strong correlation between subjective norms and continued use, whereas Nguyen and Dao (2024) reported the same for mobile banking.

Furthermore, Abubakar and Ahmad (2014) uncovered that subjective norms support technology awareness. Subjective norms positively impact customers' desire to continue using technology by providing recommendations. Bank customers who received more feedback from others, friends, and family members were more likely to use AI. Therefore, this study hypothesized the following:

H13: Subjective norms positively influence behavioral intention to use AI.

H14: Subjective norms positively influence awareness of AI.

H15: Subjective norms positively influence continuance intention to use AI.

3.9. Perceived risk

In customer research, Shi et al. (2020) defined perceived risk as related to uncertainty and consequences stemming from potential negative consequences when making decisions. In connection with AI, opportunities related to security vulnerability issues always exist, from other parties hacking and the threat of data privacy loss (Schwesig et al., 2023). In addition, AI algorithms embedded in computer systems, such as AI programs embodied in robots or chatbots, cannot distinguish and manipulate the trust of bank customers (Glikson & Woolley, 2020).

Bank customers' considering AI as insecure may decrease their usage intentions. For example, when interacting with a banking chatbot service, customers may be in an unsafe situation regarding private data, such as personal information (phone number, email, or name), being misused or shared with third parties without permission. Therefore, this study focuses on the risks customers face when interacting with technology, as customers may experience errors when using AI for transactions, which may negatively impact future behavioral and usage intentions.

Glikson and Woolley (2020) explain that customer trust and reliance on AI technology can be weak. This view is consistent with, and confirmed in, the literature, which proves the negative impact of perceived risk on the behavioral intention and sustainability of technology use. Examples include studies on online banking (Kaur & Arora, 2022), mobile banking (Saibaba, 2024), online pharmacies (Alsadoun et al., 2023), and intelligent online groceries (Thomas-Francois & Somogyi, 2023). Therefore, the following hypotheses were proposed:

H17: Perceived risk negatively affects behavioral intention to use AI.

H18: Perceived risk negatively affects continuance intention to use AI.

3.10. Moderating effect

Trust refers to customers being confident in the words, actions, and judgments of others (Tian et al., 2023). According to Gefen (2000), trust is the customer's intention in the expected outcome of the technology and the belief that the company can fulfill its responsibilities. In addition, other researchers have argued that trust can occur when customers develop confidence in a target based on their trustworthiness (Wang, Wang, et al., 2021; Wu et al., 2023). Furthermore, trust is essential for customers who feel that their rights and interests are under-protected when using technology or online transactions; thus, perceived concerns and uncertainties need to be reduced (Jiang & Lau, 2021).

In AI, trust is an initial customer confidence in technology that can help speed up transactions. Hanaysha (2022) supports this statement, explaining that trust is the main prerequisite for using technology. However, customer trust can reduce the use of technology when they simultaneously assume that its use is highly risky (Saibaba, 2024). Therefore, through empirical studies, researchers have revealed that customers with high trust tend to be willing to accept and use technology continuously (He et al., 2021; Jiang & Lau, 2021; Saibaba, 2024). When customers perceive a high risk of using technology, they avoid it (Hoque et al., 2023; Saibaba, 2024).

Mayer et al. (1995) stated, "One does not need to take any risks to trust; however, one must take risks to engage in the act of trusting." Furthermore, Mayer et al. (1995), on the relationship between trust and risk, cannot ascertain whether risk is an antecedent factor or an outcome of trust, given their interactive nature. Previous researchers have investigated whether trust and risk have a parallel relationship as regards the intent to use AI (Hasan et al., 2021; Kasilingam, 2020) and whether both affect the intention to adopt AI (Rahman et al., 2023). In addition, other researchers have proven that the relationship between trust and perceived risk is not parallel but sequential, and trust affects e-retail continuance intention (Odusanya et al., 2022), whereas trust successfully mediates the effect of perceived risk and continuance intention (Dewi & Ketut, 2020). In contrast, in a study on autonomous vehicles, risk mediated the impact of trust on intention to use (Kenesei et al., 2022). Therefore, the relationship between trust and perceived risk is complex, and the initial trust may change over time and with consumer experience (Yang et al., 2015).

Based on a review of previous research, no study has examined the role of trust as a moderator in the relationship between perceived risk and continued use of AI. Therefore, this study hypothesized the following:

H19. Perceived trust positively moderates the relationship between perceived risk and continuous intention to use AI.

4. Research method

4.1. Measurements and social disability bias

This study consisted of nine constructs, each measured by three to four items, resulting in 33 items in the model framework. Each construct's measurement is reflective, adapted from several previous researchers, and adjusted for accuracy of expression in the context of banking AI (Table 3 and Appendix). The questionnaire was prepared, and a language expert and two banking practitioners were consulted to improve the language suitability, measurement accuracy, and ease of understanding for each question.

The questionnaire comprised four sections. The first section included a statement about information confidentiality and motivated the respondents to answer the statements honestly (no wrong or correct answers). The second section included screening questions to ensure that the respondents met the sampling criteria. The third section contained the respondents' demographics, such as age, sex, education level, and occupation. Furthermore, concerning social disability bias, the research questionnaire did not include respondents' data (e-mail, name, and cell phone number) (Fisman et al., 2020; Ikhsan et al., 2024). The fourth section contained a list of questions on a Likert-type semantic differential scale, with 1 representing strongly disagree and 5 denoting strongly agree. For example, "I can easily use the AI features and services provided by the bank" for the perceived ease of use question. "I think it is a good idea to use the bank's AI features and services" for the attitude question item (Appendix). Finally, the research questionnaire was distributed online through social media platforms such as WhatsApp and Instagram for two months (February–March 2024). This distribution was aimed at gathering data from a specific group of respondents who volunteered to participate in the study without compensation.

Table 3
Latent Construct Measurement.

Construct	Item	Source
Awareness toward AI	4	Adopted from Abou-Shouk and Soliman (2021)
Perceived ease of use	4	Adapted from Asnakew (2020)
Perceived usefulness	4	Adapted from Liébana-Cabanillas et al. (2021)
Perceived risk	4	Adapted from Ben Arfi et al. (2021) and Jiang et al. (2021)
Perceived trust	4	Adapted from Liébana-Cabanillas et al. (2021)
Subjective norms	4	Adapted from Liébana-Cabanillas et al. (2021)
Attitude toward AI	3	Adapted from Asnakew (2020)
Continuance intention	3	Adapted from Rahi et al. (2021)
Behavioral intention	3	Adapted from Rahi et al. (2021)

4.2. Sampling strategy

The population in this study comprises bank customers in Indonesia in the Gen Y category. The Gen Y population was determined by their accustomed use of the internet and interest in digital technology (Isaacs et al., 2020). The total population of Gen Y in Indonesia refers to the results of the Katadata Insight Center survey (2021); 2862 Gen Y individuals have bank accounts. Therefore, the number of samples required to obtain 400 samples was determined using the Slovin formula with an error margin of 5 %. A purposive sampling approach was used, with the following criteria: having a bank account, knowing about AI, using AI features such as chatbots, mobile banking with biometric scanners (fingerprint and face recognition), and opening new accounts.

4.3. Common method bias

Common method bias (CMB) testing is conducted when researchers measure independent and dependent variables using the same response method. Therefore, CMB measurement was vital for supporting the validity of this study (Kock et al., 2021). We tested for CMB using the whole collinearity method suggested by Kock (2015) based on latent variable score (LVS) data for all constructs. Thereafter, the LVS value was regressed with its random value to produce a variance inflation factor (VIF) value. A VIF value of <3.3 (Diamantopoulos & Siguaw, 2006) declares the data accessible from collinearity problems. Table 4 presents the summary of CMB testing using SmartPLS 4.1.0.6. The VIF value for each measured variable was <3.3; thus, the research data were without collinearity problems.

4.4. Normality

Statistical hypothesis testing was performed using partial least squares−structural equation modeling (PLS-SEM) based on bootstrapping techniques (Hair Jr et al., 2022). Therefore, this technique is not affected by normal distributions. In contrast to covariance-based structural equation modeling, this technique is an option for business

Table 4
Common Method Bias.

Latent Variable Score	VIF
Attitude Toward AI	1.618
Awareness of AI	1.348
Behavioral to Adopt AI	1.695
Continuance Intention	1.791
Perceived Ease of Use	1.459
Perceived Risk	1.182
Perceived Trust	1.034
Subjective Norm	1.386
Perceived Usefulness	1.438

researchers who experience normality challenges with data (Hair, Risher, et al., 2019). However, using PLS-SEM on highly abnormal data can lead to unsatisfactory statistical significance of the parameters (Guenther et al., 2023; Hair Jr et al., 2022). Therefore, researchers using PLS-SEM should assess data normality (Sarstedt et al., 2022). Another argument is based on several considerations, such as the meaningfulness of indicator residual variances for constructs in the model (Guenther et al., 2023) and the predictive nature of the research objectives (Hair, Sarstedt, & Ringle, 2019; Ringle et al., 2023).

The normality of the data was evaluated using the Skewness and Kurtosis tests from the raw data SmartPLS 4.1.0.6, with the value limits for Skewness and Kurtosis as −2 to +2. Table 5 presents a summary of the normality test results.

Based on Table 5, some questions in each latent construct are abnormally distributed because the Skewness and Kurtosis values exceeded −2 or + 2, and some items are typically distributed. This implies that the overall data do not indicate a highly abnormal problem. Therefore, selecting PLS-SEM to answer the research hypotheses is appropriate.

4.5. Data analysis

The PLS-SEM technique with SmartPLS 4.1.0.6 software in this study was used to answer the research hypothesis. In PLS-SEM testing, two measurement models were used. The first measurement model was the outer model, which assessed the convergent validity and reliability of the questionnaire items. Convergent validity refers to the recommended outer loading value of ≥0.70 and an Average Variance Extracted (AVE) value of >0.50 for each item (Hair Jr et al., 2022). Furthermore, discriminant validity refers to the Heterotrait-Monotrait ratio of correlations (HTMT) and Fornell Lacker Criterion values (Hair Jr et al., 2022). The recommended Cronbach's alpha (CA) and Composite Reliability (CR) values are >0.70 in reliability testing. The second measurement model is the inner model, using a bootstrapping technique with 5000 subsamples. The percentile bootstrap was two-tailed testing with the confidence interval method. Bootstrapping in PLS-SEM is a resampling technique used to assess the stability and significance of an estimated model by providing confidence intervals for path coefficients. Hair Jr et al. (2022) explained that five stages must be reported in assessing the inner model: the collinearity problem, the significance of the relationship between variables, the assessment of explanatory power (R^2 and f^2), and the assessment of the structural model's predictive power using the PLSpredict method.

Table 5
Data Normality.

Variables	Indicator	Kurtosis	Skewness
Awareness of AI	AWS1	3.262	−1.586
	AWS2	0.903	−1.139
	AWS3	0.282	−0.727
	AWS4	0.906	−1.017
Perceived Ease of Use	PEOU1	0.373	−0.838
	PEOU2	0.866	−0.905
	PEOU3	1.550	−1.151
	PEOU4	0.683	−0.920
Perceived Usefulness	PU1	0.952	−1.046
	PU2	0.756	−0.962
	PU3	0.935	−1.052
	PU4	1.014	−1.041
Perceived Risk	PR1	2.586	1.641
	PR2	2.309	1.607
	PR3	2.150	1.658
	PR4	2.193	1.543
Perceived Trust	PT1	4.188	−1.854
	PT2	4.557	−1.848
	PT3	3.848	−1.785
	PT4	4.919	−1.870
Subjective Norm	SN1	1.636	−1.095
	SN2	2.015	−1.124
	SN3	1.776	−1.031
	SN4	1.777	−1.049
Attitude toward AI	ATT1	2.075	−1.283
	ATT2	1.904	−1.221
	ATT3	2.188	−1.336
Continuance Intention	CI1	4.792	−1.503
	CI2	4.942	−1.500
	CI3	3.564	−1.288
Behavioral Intention	BI1	2.127	−1.101
	BI2	1.603	−0.961
	BI3	1.137	−0.879

5. Key findings

5.1. Respondent characteristics

We targeted 400 responses from bank customers; 388 responses that met the sample criteria were obtained during the questionnaire distribution process. Therefore, the success rate of data collection was 97 %. The demographics of the respondents were obtained using the questionnaire results (Table 6). There were 186 (47.9 %) female and 202 (52.1 %) male respondents. Regarding age, 82 (21.1 %) were 28–31, 98 (25.3 %) were 32–35, 107 (27.6 %) were 36–38, and 101 (26 %) were 40–43 years old. Sixty-three respondents (16.2 %) had a high school education, 51 (13.1 %) had a diploma, 145 (37.4 %) had an undergraduate degree, 84 (21.6 %) had a postgraduate degree, and 45 (11.6) had a doctorate. Regarding the average income level, 100 (26.5 %) respondents had an income of 5000,000–10,000,000 (IDR), 123 (31.7 %) had 1,000,000–16,000,000 (IDR), 99 (25.5 %) had 17,000,000–22,000,000 (IDR), and 63 (16.2 %) had >22,000,000 (IDR). Regarding occupation, 99 (25.5 %) worked as government employees, 132 (34 %) were private entrepreneurs, 101 (26 %) were professionals, and 56 (14.4 %) were entrepreneurs.

5.2. Measurement model

The questionnaire was declared valid and reliable to answer the research objectives. Table 7 summarizes the convergent validity and reliability results. Statistically, each measurement item produces an outer loading value of >0.70 and an AVE of >0.50. These values indicate that all the measurement items reflect the measured construct. Thus, convergent validity was declared. Furthermore, each latent construct

Table 6
Respondent Characteristics.

Demographic variables	N	Percentage
Sex		
Male	202	52.1 %
Female	186	47.9 %
Age		
28–31	82	21.1 %
32–35	98	25.3 %
36–39	107	27.6 %
40–43	101	26.0 %
Education Level		
High School	63	16.2 %
Diploma	51	13.1 %
Bachelor	145	37.4 %
Postgraduate	84	21.6 %
Doctoral	45	11.6 %
Average Revenue (IDR)		
5.000.000–10.000.000	103	26.5 %
11.000.000–16.000.000	123	31.7 %
17.000.000–22.000.000	99	25.5 %
More than 22.000.000	63	16.2 %
Occupation		
Government Employee	99	25.5 %
Private Employee	132	34.0 %
Professional	101	26.0 %
Entrepreneurship	56	14.4 %

Table 7
Validity and Reliability.

Variable	Item	Outer Loading	AVE	CA	CR
	ATT1	0.856			
	ATT2	0.853			
Attitude Toward AI	ATT3	0.845	0.725	0.810	0.811
	AWS1	0.893			
	AWS2	0.801			
	AWS3	0.779			
Awareness of AI	AWS4	0.789	0.667	0.833	0.848
	BI1	0.791			
	BI2	0.803			
Behavioral Intention	BI3	0.795	0.634	0.712	0.712
	CI1	0.877			
	CI2	0.871			
Continuance Intention	CI3	0.868	0.761	0.843	0.843
	PEOU1	0.781			
	PEOU2	0.790			
	PEOU3	0.839			
Perceived Ease of Use	PEOU4	0.777	0.636	0.809	0.812
	PR1	0.852			
	PR2	0.876			
	PR3	0.869			
Perceived Risk	PR4	0.860	0.747	0.887	0.888
	PT1	0.823			
	PT2	0.816			
	PT3	0.800			
Perceived Trust	PT4	0.841	0.672	0.838	0.843
	PU1	0.812			
	PU2	0.817			
	PU3	0.838			
Perceived Usefulness	PU4	0.804	0.669	0.835	0.836
	SN1	0.756			
	SN2	0.810			
	SN3	0.787			
Subjective Norm	SN4	0.783	0.615	0.791	0.793

produced CA and CR values of >0.70, and none exceeded 0.950 (Hair Jr et al., 2022). This value indicates that each item is reliable for measuring the latent constructs.

The discriminant validity was tested using the HTMT and Fornell Lacker Criterion methods, which **Tables 8 and 9** present. We assessed discriminant validity with HTMT results in all correlation values between constructs less than 0.85 or 0.90 (Hair Jr et al., 2022). Similarly, with the Fornell Lacker Criterion test, the root AVE value was greater than the correlation between the other constructs. These results imply that the constructs with their indicators are more potent when measuring different constructs. Therefore, discriminant validity was confirmed.

5.3. Structural model

Hair Jr et al. (2022) suggested evaluating the structural model in five stages (Table 10, Table 11, and Table 12). The first stage assessed collinearity within the structural model. In Table 10, the VIF value for each path in the PLS model is <3.3 (Diamantopoulos & Siguaw, 2006) or 5 (Hair Jr et al., 2022); therefore, the structural model is free from collinearity challenges.

The second stage involved research hypothesis testing (Fig. 2 **and** Table 10). The structural equation modeling results prove that perceived ease of use (β1 = 0.352, t-value 5.380, and *p-value* < 0.001) and perceived usefulness (β2 = 0.264, t-value 4.349, and *p-value* < 0.001) have a positive and significant effect on attitude toward AI, thus accepting H1 and H2. Perceived ease of use (β5 = 0.338, t-value 5.102, and *p-value* < 0.001) and awareness of AI (β10 = 0.260, t-value 4.220, and *p-value* < 0.001) have a positive and significant effect on perceived usefulness, thus accepting H5 and H10. Additionally, subjective norms have a positive and significant impact on AI awareness (β14 = 0.399, t-value 6.060, and *p-value* < 0.001), thus accepting H14.

Perceived ease of use (β3 = 0.126, t-value 2.325, and *p-value 0.*020), perceived usefulness (β4 = 0.133, t-value 2.083, and *p-value = 0.*037), attitude toward AI (β6 = 0.306, t-value 4.400, and *p-value* < 0.001), AI awareness (β11 = 0.104, t-value 2.054, and p-*value = 0.*040), and subjective norms (β13 = 0.182, t-value 3.202, and *p-value* = 0.001) have a positive and significant effect on behavioral intention. Meanwhile, perceived risk (β17 = −0.087, t-value 2.014, and *p-value* = 0.044) negatively and significantly affects behavioral intention, thus accepting H3, H4, H6, H11, H13, and H17.

Perceived usefulness (β7 = 0.105, t-value 1.993, and *p-value* = 0.046), perceived ease of use (β8 = 0.121, t-value 2.049, and *p-value* = 0.041), attitude toward AI (β9 = 0.141, t-value 1.976, and *p-value* = *0.*048), awareness of AI (β12 = 0.089, t-value 1.983, and *p-value* = *0.*047), subjective norms (β15 = 0.143, t-value 3.069, and *p-value* = *0.*002), and behavioral intention (β16 = 0.135, t-value 2.543, and *p-value* = 0.011) have a positive and significant effect on continuance intention. Conversely, perceived risk (β18 = −0.152, t-value 3.372, and *p-value* = 0.001) negatively and significantly affects continuance intention, thus accepting H7, H8, H9, H12, H15, H16 and H18.

The third and fourth stages assess explanatory power. The R-value is used to evaluate the explanatory power of the structural model. The coefficient represents the variance in the endogenous constructs explained by all exogenous constructs (Hair Jr et al., 2022). In social science research, a low R^2 value or 0.10 is still acceptable for explaining the model, provided that the relationship between variables producing the R^2 value is significant (Ozili, 2023). Furthermore, the strength of the relationship in the structural model can be assessed using the f^2-effect size. The criteria for assessing the strength of the relationship between constructs in the structural model refer to the provisions: $f^2 = 0.02–0.14$ (weak), $f^2 = 0.15–0.34$ (moderate), and $f^2 \geq 0.35$ (strong) (Cohen, 2013).

Based on Table 11, perceived ease of use and usefulness determine 26.7 % ($R^2 = 0.267$) of bank customers' attitudes toward AI. The influence of perceived ease of use and perceived usefulness on the attitude toward AI in the structural model was weak, with f^2 values of 0.142 and 0.080, respectively. Furthermore, perceived usefulness was determined

Table 8
HTMT.

	ATT	AWS	BI	CI	PEOU	PR	PT	PU	SN	PT x PR
ATT										
AWS	0.309									
BI	0.679	0.450								
CI	0.549	0.434	0.608							
PEOU	0.563	0.272	0.539	0.511						
PR	0.289	0.297	0.336	0.397	0.266					
PT	0.106	0.072	0.101	0.202	0.125	0.052				
PU	0.490	0.401	0.537	0.478	0.481	0.191	0.097			
SN	0.359	0.488	0.532	0.491	0.320	0.196	0.071	0.400		
PT×PR	0.226	0.187	0.237	0.377	0.247	0.154	0.078	0.170	0.220	

Noted: PEOU=Perceived ease of use; PU=Perceived usefulness; ATT = Attitude toward AI; BI=Behavioral Intention; AWS = Awareness of AI; SN=Subjective norms; PR = Perceived risk; PT = Perceived Trust; CI=Continuance intention.

Table 9
Fornell Lacker Criterion.

	ATT	AWS	BI	CI	PEOU	PR	PT	PU	SN
ATT	**0.851**								
AWS	0.257	**0.817**							
BI	0.517	0.351	**0.796**						
CI	0.454	0.366	0.472	**0.872**					
PEOU	0.457	0.227	0.409	0.423	**0.797**				
PR	−0.245	−0.253	−0.269	−0.343	−0.227	**0.864**			
PT	0.086	0.054	0.069	0.171	0.102	−0.042	**0.820**		
PU	0.404	0.337	0.415	0.401	0.397	−0.165	0.061	**0.818**	
SN	0.287	0.399	0.401	0.401	0.256	−0.166	0.034	0.325	**0.784**

Noted: PEOU=Perceived ease of use; PU=Perceived usefulness; ATT = Attitude toward AI; BI=Behavioral Intention; AWS = Awareness of AI; SN=Subjective norms; PR = Perceived risk; PT = Perceived trust; CI=Continuance intention.

Table 10
Hypothesis Testing.

Hypothesis	Path	VIF	STD	STDEV	T statistics	*P* values
H1	PEOU→ATT	1.187	0.352	0.065	5.380	<0.001
H2	PU → ATT	1.187	0.264	0.061	4.349	<0.001
H3	PEOU→BI	1.385	0.126	0.054	2.325	0.020
H4	PU → BI	1.389	0.133	0.064	2.083	0.037
H5	PEOU→PU	1.054	0.338	0.066	5.102	<0.001
H6	ATT → BI	1.421	0.306	0.069	4.400	<0.001
H7	PU → CI	1.418	0.105	0.053	1.993	0.046
H8	PEOU→CI	1.433	0.121	0.059	2.049	0.041
H9	ATT → CI	1.583	0.141	0.072	1.976	0.048
H10	AWS → PU	1.054	0.260	0.062	4.220	<0.001
H11	AWS → BI	1.311	0.104	0.051	2.054	0.040
H12	AWS → CI	1.334	0.089	0.045	1.983	0.047
H13	SN → BI	1.284	0.182	0.057	3.202	0.001
H14	SN → AWS	1.000	0.399	0.066	6.060	<0.001
H15	SN → CI	1.349	0.143	0.046	3.069	0.002
H16	BI→CI	1.663	0.135	0.053	2.543	0.011
H17	PR → BI	1.124	−0.087	0.043	2.014	0.044
H18	PR → CI	1.140	−0.152	0.045	3.372	0.001

Noted: PEOU=Perceived ease of use; PU=Perceived usefulness; ATT = Attitude toward AI; BI=Behavioral Intention; AWS = Awareness of AI; SN=Subjective norms; PR = Perceived risk; PT = Perceived trust; CI=Continuance intention.

Table 11
R-Square and F-Square.

Path	R^2	f^2	Decision
Perceived ease of use→Attitude toward AI	0.267	0.142	Weak
Perceived usefulness→Attitude toward AI		0.080	Weak
Perceived ease of use→Perceived usefulness	0.222	0.139	Weak
Awareness of AI→Perceived usefulness		0.083	Weak
Subjective norms→Awareness of AI	0.159	0.189	Moderate
Perceived ease of use→Behavioral intention	0.398	0.019	Very Weak
Perceived usefulness→Behavioral intention		0.021	Weak
Attitude toward AI→Behavioral intention		0.109	Weak
Awareness of AI→Behavioral intention		0.014	Very Weak
Subjective norms→Behavioral intention		0.043	Weak
Perceived risk→Behavioral intention		0.011	Very Weak
Awareness of AI→Continuance intention	0.442	0.011	Very Weak
Subjective norms→Continuance intention		0.027	Weak
Behavioral intention→Continuance intention		0.020	Weak
Perceived usefulness→Continuance intention		0.014	Very Weak
Perceived ease of use→Continuance intention		0.018	Very Weak
Attitude toward AI→Continuance intention		0.023	Weak
Perceived risk→Continuance intention		0.036	Weak
Perceived trus x perceived risk→Continuance intention		0.051	Weak

by 22.2 % ($R^2 = 0.222$) of perceived ease of use and bank customers' awareness of AI technology. The influence of perceived ease of use and awareness toward AI on perceived usefulness in the structural model was weak, with f^2 values of 0.139 and 0.083, respectively. The AI awareness of bank customers was determined by 15.9 % ($R^2 = 0.159$) of the subjective norms. The strength of the influence of subjective norms on bank customers' AI awareness in the structural model is moderate, with an f^2 value of 0.189.

Table 12
PLSpredict.

	Q^2predict	MAE		
		PLS-SEM	LM	PLS SEM-LM
ATT1	0.154	0.623	0.664	−0.041
ATT2	0.139	0.630	0.658	−0.028
ATT3	0.149	0.628	0.660	−0.032
AWS1	0.127	0.505	0.548	−0.043
AWS2	0.102	0.771	0.783	−0.012
AWS3	0.083	0.766	0.762	0.004
AWS4	0.064	0.719	0.754	−0.035
BI1	0.174	0.558	0.593	−0.035
BI2	0.150	0.615	0.646	−0.031
BI3	0.150	0.667	0.693	−0.026
CI1	0.271	0.448	0.491	−0.043
CI2	0.258	0.434	0.473	−0.039
CI3	0.219	0.491	0.522	−0.031
PU1	0.102	0.726	0.752	−0.026
PU2	0.102	0.761	0.779	−0.018
PU3	0.131	0.719	0.747	−0.028
PU4	0.142	0.699	0.726	−0.027

Bank customers' behavioral intentions toward AI were determined by their perceived ease of use, perceived usefulness, attitude toward AI, AI awareness, subjective norms, and perceived risk at 39.8 % ($R^2 = 0.398$). The strengths of the influence of perceived ease of use, awareness toward AI, and perceived risk on behavioral intention in the structural model are fragile, with *f* values of <0.02 (0.019, 0.014, and 0.011). The paths of perceived usefulness, attitude toward AI, and subjective norms with behavioral intention explain the weak influence, with f^2 values of 0.021, 0.109, and 0.043.

Bank customers' intentions to continue using AI technology were determined by 44.2 % ($R^2 = 0.442$) of AI awareness, subjective norms, behavioral intention, perceived usefulness, perceived ease of use, attitudes toward AI, and perceived risk. The strengths of the influence of AI awareness, perceived usefulness, and perceived ease of use with continuance intention in the structural model are fragile, with *f* values of <0.02 (0.011, 0.014, and 0.018). The paths of subjective norms, behavioral intention, attitude toward AI, and perceived risk with continuance intention explain the weak influence, with respective f^2 values of 0.027, 0.020, 0.023, and 0.036, respectively.

The final step in assessing the structural model was predictive power with partial least-squares prediction. This study follows the recommendations of Shmueli et al. (2019) to assess the predictive performance of the structural model out of the sample by focusing on endogenous constructs. Partial least-squares prediction testing is crucial because a model that fits the research sample does not necessarily predict outcomes well for data outside the sample (Hair Jr, 2021). Referring to

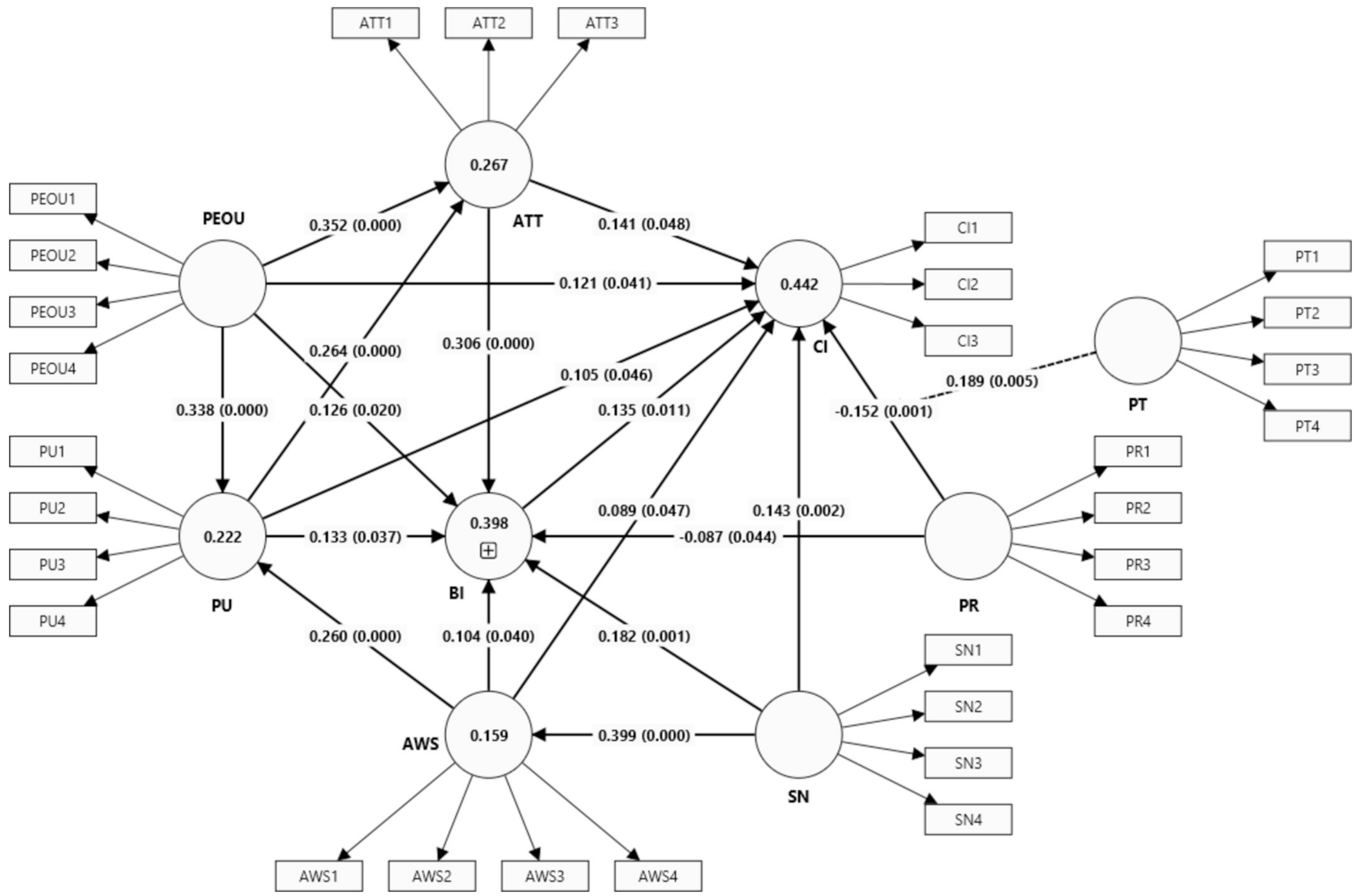

Fig. 2. Structural Model Testing.

Table 12, we evaluated the out-of-sample prediction performance of the structural model using the mean absolute error (MAE) by comparing the MAE values in PLS-SEM and the Linear Model (LM). The criterion for determining the prediction strength is that the MAE value in PLS-SEM must be smaller than in LM (Shmueli et al., 2019). Consequently, almost all indicators of the endogenous constructs produced PLS-SEM < LM values. The structural model has moderate predictability for out-of-sample or new observations. In other words, PLS-predict evaluates the model performance more comprehensively. Furthermore, the structural model has good predictive power within the sample because the Q^2 value predicts >0 for each endogenous construct indicator.

5.4. Moderation effect

Testing the moderating role of perceived trust is illustrated in the interaction model between perceived risk and perceived trust in the continuance intention to use AI in banking. Based on Table 13, the interaction between perceived risk and perceived trust with continuance intention is positive and significant (β19 = 0.189, t-value 2.832, and *p-value* 0.005), thus accepting H19. The path coefficient of the moderation interaction was positive, explaining why perceived trust positively moderates the relationship between perceived risk and the continuance intention to use AI in banking. Overall, perceived trust reduces the negative relationship between perceived risk and the continuance intention to use AI in banking.

Table 13
Moderating Effect.

		VIF-Inner	STD	STDEV	T statistics	P values
H19	PT → CI	1.015	0.103	0.047	2.178	0.029
	PT x PR → CI	1.096	0.189	0.067	2.832	0.005

Furthermore, the interaction plot was illustrated using the procedure of Ringle et al. (2024) to understand the interaction pattern between perceived risk and continuance intention by calculating the slope of one standard deviation above (+1 SD) and below the mean perceived trust (−1 SD). Fig. 3 illustrates the three lines representing the interaction effects of perceived trust at the three levels. The red line indicates the relationship between perceived risk and continuance intention when the customer's perceived trust is one standard deviation below the mean (−1 SD). The decreasing line denotes that customer-perceived risk has a negative relationship with the intention to continue using AI in the banking sector when perceived trust is low.

The blue line indicates the relationship between perceived risk and continuance intention when perceived trust is at its mean value. The green line indicates the relationship when the customer's perceived trust is one standard deviation above the mean (+1 SD). Lines that flatten or rise slightly indicate that customers with higher levels of perceived trust and perceived risk have a somewhat positive relationship with their intention to continue using AI. Therefore, the lines in Fig. 3 visually represent the main findings of the study, which reveal that the effect of perceived risk on continuance intention using AI is not constant. However, this may vary with the level of perceived trust. When customers' perceived trust is low (red line), increased perceived risk tends to significantly decrease the intention to continue using AI. Conversely, when customers' perceived trust is high (green line), an increase in perceived risk has a slightly positive relationship with the continuance intention to use AI. Therefore, the moderation effect is vital for strengthening the clarity and understanding of the results, emphasizing that perceived trust significantly affects the direction and strength of the

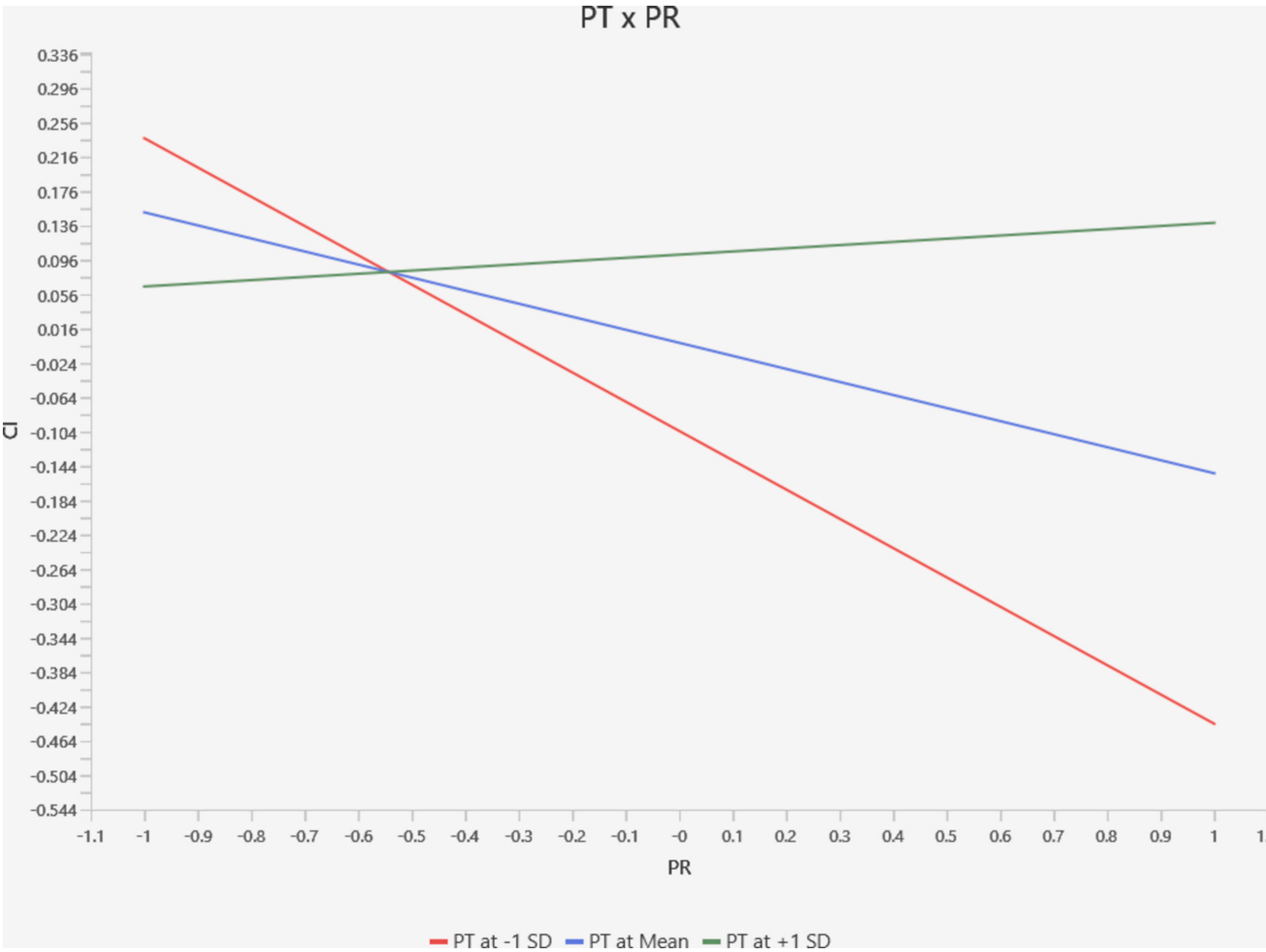

Fig. 3. Simple Slop Moderating Effect.

relationship between perceived risk and the intention to continue using AI.

6. Discussion

6.1. Theoretical implications of the TAM model

This study solved all the hypotheses; thus, the findings of this multidisciplinary research contribute to the literature on customer behavior in adopting technology, especially AI, in banking. This study proposes an extended TAM framework with the constructs of AI awareness, subjective norms, perceived risk, and perceived trust as moderators. The empirical results of this study explain the positive contribution of the expanded TAM framework in influencing behavioral and continuance intentions to use AI in the banking sector.

Perceived ease of use and perceived usefulness positively and significantly affected attitudes toward AI. This finding explains why customers' positive attitudes toward AI can be determined by how easy it is to use the technology and its usefulness in supporting transaction activities and banking services. These statements and findings have been confirmed by several researchers in the technology adoption context (Foroughi et al., 2024; Kashive et al., 2021; Rahi et al., 2021;Rahman et al., 2023; Roy et al., 2022; Wang, Liu, & Tu, 2021). Furthermore, this study proves that perceived ease of use positively and significantly affects perceived usefulness. This finding indicates that customers who find technology easy to operate consider it beneficial. For example, the ease of using the chatbot feature to discuss banking information and services with customer service makes customers feel that it is helpful because it simplifies the discussion. This statement supports the findings of previous studies on technology use (Abdullah & Almaqtari, 2024; Damerji & Salimi, 2021; Foroughi et al., 2024; Roy et al., 2022; Singh, Sahni, & Kovid, 2020; Wang, Liu, & Tu, 2021). Within the TAM framework, behavioral intention is positively and significantly determined by the perceived ease of use, usefulness, and attitude toward AI. The results of this hypothesis explain that the positive attitude of customers formed after feeling that AI is easy to use and valuable significantly impacts customer behavior in accepting this technology. The results of this study follow the findings of previous researchers who proved that the perceived ease of use of AI (Abdullah & Almaqtari, 2024; Jnr & Petersen, 2023; Liu et al., 2022; Liu & Luo, 2021; Singh, Sahni, & Kovid, 2020; Singh, Sinha, & Liébana-Cabanillas, 2020), perceived usefulness (Liu et al., 2022; Liu & Luo, 2021; Richter et al., 2023; Singh & Sinha, 2020; Singh, Sinha, & Liébana-Cabanillas, 2020; Wang, Liu, & Tu, 2021) and attitude toward AI impact behavioral intention to use it (Rahman et al., 2023; Roy et al., 2022; Wang, Liu, & Tu, 2021).

This study also proves that perceived ease of use, usefulness, attitude toward AI, and behavioral intention positively and significantly affect the continuance intention of AI in the banking sector. These findings strengthen the concept of TAM as an initial technology acceptance model. In addition, insights from TAM are critical for understanding customers' long-term loyalty and engagement with AI. This finding is consistent with several previous studies that examined the effects of perceived ease of use (Ashfaq et al., 2020; Singh, Sahni, & Kovid, 2020), perceived usefulness (Ashfaq et al., 2020; Cho & Lee, 2020; Liébana-

Cabanillas et al., 2021; Rahi et al., 2021; Richter et al., 2023), attitude toward AI (Foroughi et al., 2024; Rahi et al., 2021) and behavioral intention toward continuance intention in using technology (Chatterjee et al., 2021; Lin, 2017).

6.2. Theoretical implications of the extended TAM model

This study also explored the extension of antecedents from the TAM framework, such as AI awareness, subjective norms, perceived risk, and perceived trust, as moderators between perceived risk and continuance intention. The first antecedent was AI awareness. This study revealed that AI awareness has a positive and significant effect on perceived usefulness, behavioral intention, and continuance intention. This finding indicates that customers who are aware of AI can support transactions and quickly access all banking AI features. They find technology useful and that it can help them complete their tasks quickly. Ultimately, the awareness of the importance of adopting AI affects customers' willingness to continue using it.

Furthermore, AI awareness involves customers' understanding of its abilities, application, and added value to support the goal of using AI technology. AI awareness hypothesis significantly affects perceived usefulness. This is consistent with the study of Singh and Sinha (2020) on mobile wallets, while the effect of AI awareness on behavioral intention is consistent with the study of Shahzad et al. (2024) on adopting cryptocurrency and that of Alsadoun et al. (2023) on using online pharmacies. AI awareness affects the continuance intention, aligning with the study by Nguyen et al. (2024) on adopting e-payment.

The second antecedent is the subjective norm. This study uncovered that subjective norms positively and significantly affect behavioral intention, AI awareness, and continuance intention. This finding explains that subjective norms create a social and cultural context that can shape customer awareness, behavioral intentions, and continuance intentions in banking AI technology. Thus, subjective norms influence how customers become aware of AI technologies through social pressure, peer recommendations, and community discussions. Concerning behavioral intentions, subjective norms can create social pressure and encourage customers to adopt AI technologies with the support of social expectations, approval, and role-model behavior. Finally, subjective norms help customers decide to continue using AI technologies based on social pressure, positive reinforcement, and norms that apply to them. Empirically, this finding supports that of Rahman et al. (2023) in the context of AI banking, explaining that subjective norms positively impact behavioral intention. Similarly, Roy et al. (2022) conducted a study on AI robots in educational systems.

Furthermore, subjective norms have a positive and significant effect on AI awareness, which Abubakar and Ahmad (2014) confirmed in a previous study. Owing to the lack of subjective norm studies on awareness in the context of technology adoption, the results of this study contribute to the literature regarding subjective norms on AI awareness. Subjective norms have a positive and significant effect on continuance-intention, consistent with the findings of several previous studies, such as those of Liébana-Cabanillas et al. (2021) on the use of near field communication (NFC) in mobile banking, Singh, Sinha, and Liébana-Cabanillas (2020) on adopting mobile wallets, and Huang (2020) on using social mind tools in education.

The third antecedent was perceived risk. This study observed that perceived risk negatively and significantly affects behavioral and continuance intentions. This finding explains why customers who perceive high risks in using AI technology, such as privacy violations, security threats, or financial losses, may experience reduced behavioral intentions and stop adopting it. Fear of the negative consequences of using AI technology may cause customers to hesitate or avoid it. In addition, a high perceived risk can create uncertainty and doubt about the safety of a technology. For example, if customers are uncertain about the reliability or accuracy of banking AI technology, they will be reluctant to use it.

Furthermore, customers prefer to avoid risks and protect themselves from potential losses. Therefore, customers deliberately disconnect from banking AI technology to avoid adverse outcomes. Previous studies support this explanation, such as that of Thomas-Francois and Somogyi (2023) in the context of online grocery stores, which uncovered that perceived risk negatively and significantly impacts behavioral intention. Kaur and Arora (2022) reported similar results. Furthermore, Liébana-Cabanillas et al. (2021) studied the use of NFC mobile payments and uncovered that perceived risk negatively and significantly affected continuance intention. Likewise, Poromatikul et al. (2020) and Timur et al. (2023) explained the same findings in the context of mobile banking and online food delivery, respectively.

Assessing the moderating role of perceived trust, the interaction between perceived risk and perceived trust and continuance intention was positive and significant. These results reveal that perceived trust positively moderates the relationship between perceived risk and the continuance intention to use AI technology in banking. This finding provides new insights into the TAM because no empirical study has proven that perceived trust moderates the relationship between perceived risk and continuance intentions. However, perceived trust positively and significantly moderates the relationship between behavioral and continuance intention (Nguyen & Dao, 2024) and between perceived risk and behavioral intention positively and significantly (Kaur & Arora, 2020).

6.3. Managerial implications

The findings of this study contribute to the implementation of AI strategies in the banking sectors of developing countries, particularly the Indonesian government, to manage and develop AI technology. First, the TAM framework, which consists of perceived ease of use, perceived usefulness, attitude, behavioral intention, and continuance intention, was substantially influential in this study. This finding signals to bank management that the TAM framework can predict and ensure customer sustainability in adopting AI technology as an investment in support services.

Regarding perceived usefulness and perceived ease of use, the bank management needs to socialize and demonstrate how AI can improve transaction and service efficiency, reduce costs, and enhance customer experience to ensure a positive attitude and intention to continue use. This is consistent with the study by Chatterjee et al. (2020), which explained that employees in India who use AI-based customer relationship management technology can improve their performance and work more effectively. Another implementation is for banks to create dedicated web pages explaining how AI is used in various services, such as chatbots used for customer service in India (Mehrolia et al., 2023) or intelligent fraud detection systems. This supports customers' understanding that AI is used to improve their services and security and not to exploit their data. Another example is educating customers on how AI works through online content that explains the benefits and security measures in place. Trials of AI systems can be provided, where customers can learn about digital security and how AI helps detect fraud, as suggested in a qualitative study by Mogaji et al. (2021) in Nigeria and Vietnam. In addition, Rahman et al. (2023) uncovered that privacy and data security issues are significant barriers to technology adoption in Malaysia due to concerns over potential personal data breaches and cybersecurity risks. Meanwhile, in India, AI technology adoption is still in the developmental stage; therefore, security and privacy issues are gaining importance mainly because of the risks and challenges related to personal data protection and information security (Chatterjee et al., 2021). An Ipsos (2015) study in Nigeria reported that consumers are highly suspicious of online transactions owing to the high level of cybercrime in the country. Spamming has also been reported as a common activity in Nigeria, and many consumers believe that they are vulnerable to identity theft when transacting online (Wang et al., 2020). Consequently, consumers' perceived risks when interacting with the internet discourage them from adopting Internet-based technological innovations.

Furthermore, for AI to be sustainably used by customers, bank management in developing countries, specifically Indonesia, should focus on designing intuitive and easy-to-understand interfaces, providing robust security systems to protect customer data, and adapting to the latest developments. This is consistent with the findings of Yüksel et al. (2023), which explained that a responsive and user-friendly design is essential to ensure that Turkish users from various backgrounds can access and use AI technologies effectively. In addition, AI technology should be less complex for ease of understanding and use. The bank management also requires technical support to address customer issues while interacting with AI features. Furthermore, support is needed from the bank management to shape customers' positive attitudes and behavioral intentions toward AI. For example, banks should adopt a technology/innovation-oriented vision to support their banking services. Banks in India integrate AI initiatives with business strategies to create customer experiences and service innovation (Bag et al., 2022). Additionally, it provides a framework for policies and standard procedures for using AI, including ethics, data security, and legal compliance, as in South Africa (Akinbowale et al., 2024). Banks must integrate AI technologies with current systems to support smooth processes and customer interactions with AI-based machines. Customer feedback and AI technology iterations should also be assessed to make adjustments and improvements to suit customer needs.

Regarding the extended constructs of the TAM, this study uncovers that subjective norms, perceived risk, and awareness toward AI significantly affect behavioral and continuance intentions. Similarly, perceived trust positively moderates the relationship between perceived risk and continuance intention. These findings provide the bank management with an understanding of the importance of these four constructs in assessing customer behavior toward using AI technology.

In addition to being self-driven, a customer's decision to continue or stop using AI technology is determined by the views and opinions of surrounding individuals, such as friends, family, and those considered essential to the customer (bank leaders or observers). For example, a closed culture that values privacy will likely reject AI, whereas an open culture will accept it. From the perspective of the reference group, AI technology can be a threat or innovation that can influence customer attitudes and behaviors. Suppose that AI technology is perceived as a threat; in that case, the bank management will face challenges and barriers from customers when adopting it. However, if AI technology is perceived as good and beneficial to customers, the awareness and trust in the technology will increase, improving the bank's reputation. Customer attitudes toward accepting technological changes also affect the successful implementation of AI technology in the banking sector. Therefore, subjective norm studies are necessary for bank management to build social and cultural support for AI technology, reduce resistance, and facilitate its successful adoption.

Increasing customer awareness is crucial in ensuring the successful adoption of AI. For instance, the bank management should conduct campaigns through online channels (social media, email, websites, and advertisements) to educate customers on the use and benefits of AI to support banking services. This will make customers feel more comfortable and understand how AI functions. Therefore, AI awareness is essential in the TAM framework for predicting its acceptance in the banking sector.

The bank management and customers face concerns and challenges regarding the perceived risks of AI. For example, AI involves sensitive data (such as personal and financial information) that irresponsible parties can access through cyberattacks. Therefore, data security is a challenge that requires special attention from bank management in countries such as Vietnam and other developing countries (Thach et al., 2021). This can be resolved by providing precise and comprehensive information on the security of the AI technology used by customers and concrete steps to secure customer information. Two-way authentication, encryption, and biometric authentication are top practices for such security measures. Customers should also be educated about security and personal data issues. When customers encounter a challenge or are suspicious, they must immediately notify the bank and resolve it. Banks also need to provide customer service to address security-related issues. In addition, the bank management should develop a system to inform customers concerning fraud, the use of unauthenticated data, and steps to resolve fraud.

Trust is a positive moderating factor in the effect of perceived risk on the intention to continue using AI. This study's findings imply that when customers trust in banking AI technology, the negative impact of perceived risk on the intention to continue using AI technology can be suppressed. Therefore, building customer trust to reduce the negative impact of perceived risk is essential, even though customers are aware of the risks they face. High trust makes them confident about continuing to use AI in the banking sector.

Considering the findings of this study, the bank management needs to implement effective managerial policies to build customers' trust in the short and long term. Recommendations for short-term policy:

First, customer data can be protected using robust encryption protocols to prevent unauthorized access. Second, privacy regulations (general data protection regulations) should be complied with to ensure customer data management. Third, all AI algorithms should be unbiased by conducting regular audits to evaluate the AI systems. AI system audits can also help banks maintain their reputations for AI technology and customer trust. Fourth, the AI technology must be tested and validated before implementation. This step aims to minimize the errors caused by the system, allowing banks to identify and address potential challenges before the technology is widely implemented. This strengthens customer confidence regarding the reliability of the AI technology.

Recommendations for long-term policies:

First, AI should be integrated with blockchain technology to ensure greater transparency, efficiency, and security in financial transactions. Second, digital platforms should be developed to create personalized experiences and customer recommendations through in-depth big data analysis, providing relevant product and service offerings in real-time. Third, concerning ethics, Indonesian banks and governments need to develop policy frameworks and ethical practices for using AI, such as ensuring that it is not discriminated against in credit scoring or access to services. Through these policies, bank management can build and maintain customer trust to mitigate the impact of perceived risks and make customers feel confident in continuing to use AI technology in their banking services.

Finally, by applying the TAM framework, banks can encourage customers to continue adopting AI technologies and maximize their long-term benefits with the support of awareness, subjective norms, perceived risk, and perceived trust factors.

7. Conclusion, limitation, and future research

This study focused on the TAM framework to investigate its relationship with subjective norms, AI awareness, perceived risk, and perceived trust as extensions of the model as regards AI technology adoption in the banking sector. In conclusion, this study uncovered the importance of the TAM framework and some of its extension factors for the Indonesian banking sector to implement AI. Furthermore, this study provides insights for the banking industry in Indonesia to increase the adoption and continuance intention of AI technology, such as increasing the ease of technology use, perceived benefits, the contribution of subjective norms, building attitudes toward and awareness of AI technology, and lowering customers' perceived risks. In addition, this study provides further insight into the importance of perceived trust in moderating the relationship between perceived risk and continuance intention. However, this study has limitations that researchers need to examine thoroughly. For example, it focused only on a sample from the millennial generation in Indonesia. Therefore, future research should compare generations (Gen X and Gen Z) to obtain more comprehensive generalizations. Cross-cultural studies and sex comparisons should be explored in future research to provide deeper insights into the relationship between constructs and their impact on sustainable behavior in AI technologies. Overall, this study expands the literature on the adoption and sustained use of AI technologies in the banking sector and contributes to increasing the adoption and sustained use of AI technologies in serving customers to aid the development of banking strategies in Indonesia.

CRediT authorship contribution statement

Ridho Bramulya Ikhsan: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Yudi Fernando:** Writing – review & editing. **Hartiwi Prabowo:** Resources, Conceptualization. **Yuniarty:** Conceptualization. **Anderes Gui:** Validation, Project administration, Formal analysis, Data curation. **Engkos Achmad Kuncoro:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors convey their appreciation to the Research and Technology Transfer Office, Bina Nusantara University, for the Initiative Projects Grant: Contract number: 0248/SK/Proyek Inisiatif-UBN/XII/2023, and contract period: January–December 2024.

Appendix A. Appendix

Research Questionnaire

Awareness of AI = Adopted from Abou-Shouk and Soliman (2021).

AWS1. I want to learn more about banks' AI features and services.

AWS2. I will pay more attention to banks that provide AI features and services.

AWS3. AI features and services in banking attract my attention.

AWS4. I am highly concentrated on AI features and services provided by banks.

Perceived ease of use = Adapted from Asnakew (2020).

PEOU1. I can easily use AI features and services provided by the bank.

PEOU2. The bank's AI features and services are easily accessible to me.

PEOU3. I quickly learn how to use the AI features and services provided by the bank.

PEOU4. I find the bank's AI features and services are appropriate for my transactions.

Perceived Usefulness = Adapted from Liébana-Cabanillas et al. (2021).

PU1. Using AI features and services can help me perform banking transactions.

PU2. Using AI features and services can increase efficiency in conducting banking transactions.

PU3. Using AI features and services for banking transactions can increase my productivity.

PU4. In general, AI features and services can help me with banking transactions.

Perceived Risk = Adapted from Ben Arfi et al. (2021) and Jiang et al. (2021).

PR1. Using AI features and services for banking transactions is risky.

PR2. Using AI tools and services for banking transactions will cause problems if something goes wrong.

PR3. I will make a mistake using AI features and services for banking transactions.

PR4. I feel worried about losing personal data.

Perceived Trust = Adapted from Liébana-Cabanillas et al. (2021).

PT1. Banks will keep their promises and commitments to AI features and services.

PT2. AI features and services are trustworthy.

PT3. I will convince myself that AI features and services are reliable systems.

PT4. The bank will take responsibility for AI features and services.

Subjective Norm = Adapted from Liébana-Cabanillas et al. (2021).

SN1. The people whose opinions I value will approve if I use AI features and services for banking transactions.

SN2. Most people I have in mind think I should use AI features and services for banking transactions.

SN3. They expect me to use AI features and services for banking transactions.

SN4. The people closest to me will agree if I use AI features and services for banking transactions.

Attitude toward AI = Adapted from Asnakew (2020).

ATT1. I think using the bank's AI features and services is a good idea.

ATT2. I think using the bank's AI features and services is fun.

ATT3. Using the bank's AI features and services for banking transactions is a desirable

Continuance Intention = Adapted from Rahi et al. (2021).

CI1. I intend to continue using the bank's AI features and services rather than traditional ones.

CI2. I want to continue using the bank's AI features and services as often as possible.

CI3. I intend to continue using the bank's AI features and services rather than discontinuing them.

Behavioral Intention = Adapted from Rahi et al. (2021).

BI1. I will use the bank's AI features and services regularly in the future.

BI2. I recommend that others use AI banking features and services.

BI3. I intend to use AI features and services to access my bank information easily.

Interview Questions

1. How do you respond to AI adoption in Indonesia's banking sector, especially regarding risk and customer trust?
2. What do you think about data privacy and security issues when customers interact with AI technology? Is there a role of the customer's social group regarding AI technology?
3. What do you think about the availability of internet infrastructure in Indonesia? What is the level of digital literacy of customers in Indonesia?
4. What is your response regarding policies and regulations on AI, especially in the banking sector?

Data availability

I have shared the link to my data 10.6084/m9.figshare.27686706

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