

*Research Article*

# Empirical Partial Least Squares Structural Equation Modeling Study on the Continued Use of Generative AI Assistants in Digital Banking: The Moderating Role of Digital Financial Literacy in Vietnam

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**Abstract:** The rapid integration of generative artificial intelligence (GenAI) assistants into digital banking services has transformed customer interactions; however, sustaining users' continued use of these technologies remains a critical challenge, particularly in emerging markets. Drawing on the perspectives of trustworthy AI and technology continuance, this study investigates the technological and behavioral drivers of the continued use of generative AI assistants in digital banking while examining the moderating role of digital financial literacy in Vietnam. A mixed-method research design was employed. First, a qualitative phase involving in-depth discussions with 35 experts in digital banking was conducted to refine and validate the measurement scales. A large-scale quantitative survey was administered to customers who regularly use digital banking services. From 900 distributed questionnaires, 845 valid responses were collected and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0. The results demonstrate that explainable AI, AI service quality, perceived cybersecurity assurance, perceived AI accuracy and reliability, and perceived privacy protection significantly influence users' continuance intention and trust in generative AI assistants. AI service quality emerged as the strongest predictor of trust ( $\beta = 0.548$ ) and continuance intention ( $\beta = 0.281$ ). Trust plays a central mediating role, significantly enhancing the intention of users to continue using GenAI assistants in digital banking. Furthermore, the findings reveal a significant moderating effect of digital financial literacy on the relationship between trust and continuance intention, indicating that users with higher levels of digital financial literacy are better able to translate trust into sustained usage behavior. This study contributes to the literature on continuance intention and AI trust by extending existing AI adoption frameworks from initial acceptance to sustained use of GenAI assistants in digital banking. It offers an integrated model that combines trustworthy AI attributes, trust, and digital financial literacy, thereby clarifying how technological quality and user capability jointly shape continuance intention in an emerging market. The findings provide practical implications for banks and policymakers by emphasizing AI service quality, transparency, cybersecurity assurance, privacy protection, and digital financial education as key levers for GenAI adoption.

**Keywords:** Continuance intention; Digital banking; Digital financial literacy; Generative artificial intelligence; Trust

## 1. Introduction

The rapid advancement of digital technologies has profoundly reshaped the global financial sector, with digital banking emerging as a central pillar of contemporary financial services. In recent years, the integration of artificial intelligence (AI) into banking operations has accelerated, driven by the need to enhance service efficiency, personalize customer interactions, and manage the growing volume of real-time data (Abad-Segura et al., 2020; Milana & Ashta, 2021). Among

various AI applications, generative AI (GenAI) assistants, such as AI-powered chatbots and virtual financial advisors, have gained particular prominence in digital banking due to their ability to generate human-like responses, provide contextualized recommendations, and support complex customer inquiries (Adam et al., 2021; Al-Halbusi et al., 2023; Cao & Zhai, 2022).

While prior studies have extensively examined the initial adoption of AI-based technologies in financial services, sustaining users' continued use remains a critical yet underexplored challenge, especially in emerging economies (Lee et al., 2023; Mfumbilwa et al., 2024). Continued use, often conceptualized as continuance intention, reflects users' willingness to continue using a technology after initial adoption and is essential for realizing long-term value from digital transformation investments (Lee et al., 2023). Understanding the determinants of continued use of GenAI assistants becomes particularly important in the context of digital banking, where switching costs are low and customer trust is fragile.

The success of AI-enabled services depends not only on technological sophistication but also on users' perceptions of trustworthiness, security, and ethical governance (Bedué & Fritzsche, 2022; Choung et al., 2023). Unlike traditional information systems, GenAI systems operate with a high degree of autonomy and opacity, raising concerns about their explainability, data privacy, cybersecurity risks, and output reliability (Al-Dosari et al., 2024). These concerns are amplified in the financial domain, where AI systems process highly sensitive personal and financial data and directly influence users' financial decisions (Ashraf et al., 2025; Grout, 2021).

Among emerging markets, Vietnam provides a compelling research context. The country has experienced rapid growth in digital banking adoption, driven by widespread smartphone penetration, government-led digital transformation initiatives, and the expansion of fintech ecosystems (Abad-Segura et al., 2020; Mhlanga & Mhlanga, 2020). However, disparities in digital skills and financial literacy persist, potentially shaping how users perceive and interact with AI-enabled banking services (Hussain et al., 2025; Odei-Appiah et al., 2022). These characteristics make Vietnam an ideal setting for investigating the interplay among technological factors, trust, and user capabilities in shaping the continued use of GenAI assistants.

Compared with several emerging markets, Vietnam offers a distinctive context because digital banking adoption has grown rapidly alongside uneven levels of digital and financial literacy. Similar to other emerging economies, users benefit from expanding fintech infrastructure but remain exposed to cybersecurity awareness, data privacy, and limited experience with AI-based financial advice. This combination makes Vietnam an appropriate empirical setting for examining whether users' digital financial literacy strengthens or constricts trust in GenAI banking assistants. Therefore, the Vietnamese case provides insights relevant to other emerging markets undergoing rapid digital financial transformation.

**Generative AI and Digital Banking:** Artificial intelligence (AI) technologies have become integral to modern banking, supporting functions ranging from fraud detection and credit scoring to customer service automation and personalized financial advice (Cao & Zhai, 2022; Milana & Ashta, 2021). GenAI assistants represent a new generation of AI applications that go beyond rule-based or retrieval-based chatbots by generating adaptive, context-aware responses. Previous research indicates that such systems can significantly enhance customer experience by improving response speed, availability, and personalization (Adam et al., 2021; Cheng & Jiang, 2022).

Despite these advantages, GenAI deployment in banking introduces unique challenges. Concerns over AI accuracy, hallucination, and inconsistent outputs can undermine users' confidence in AI-generated financial advice (Bedué & Fritzsche, 2022). Furthermore, GenAI systems often rely on large-scale data processing, intensifying cybersecurity and privacy protection concerns (Butler et al., 2023; Rana et al., 2020). Understanding how users evaluate these technological attributes is essential for explaining both trust formation and continued usage behavior (Chinoda & Kapingura, 2024).

**Trust as a Central Mechanism in Artificial Intelligence-enabled Banking:** Trust has long been recognized as a fundamental mechanism governing technology acceptance and

continued use, particularly in contexts characterized by uncertainty and perceived risk (Ajzen, 2020; Lee et al., 2023; Mohammed & Mirlam, 2026).

The literature on AI trust emphasizes multiple dimensions, including perceived competence, reliability, transparency, and ethical alignment (Bedué & Fritzsche, 2022; Choung et al., 2023). Some scholars caution against anthropomorphizing trust in human–AI relationships (Al, 2023). However, trust is commonly conceptualized at the system or service level in service contexts such as digital banking, referring to users' confidence that AI-enabled services will perform as expected and safeguard their interests (Lee et al., 2023; Mfumbilwa et al., 2024). This study adopts this pragmatic perspective, focusing on trust in GenAI assistants rather than interpersonal trust as part of digital banking services (Bernards & Campbell-Verduyn, 2019).

**Explainable AI (XAI):** XAI refers to the extent to which AI systems provide understandable and transparent explanations for their outputs and recommendations. In financial services, explainability is increasingly seen as a prerequisite for trustworthy AI, particularly given regulatory and ethical considerations (Butler et al., 2023). Empirical studies suggest that greater explainability enhances users' understanding and confidence in artificial intelligence (AI) systems, thereby fostering trust and acceptance (Bedué & Fritzsche, 2022). Accordingly, this study posits that explainable artificial intelligence (AI) positively influences trust and continuance intention.

**AI Service Quality (AISQ):** AISQ captures users' perceptions of the overall performance of AI-enabled services, including responsiveness, usefulness, and personalization (Juvina et al., 2019). Prior research consistently identified service quality as a strong determinant of trust and continued use in AI-based customer service and chatbot contexts (Adam et al., 2021; Dawar et al., 2022). In digital banking, high AI service quality signals competence and reliability, reinforcing trust and encouraging sustained engagement (Dahmani et al., 2023). From a critical perspective, XAI functions as a mechanism to reduce information asymmetry and strengthen perceived accountability in AI-driven banking. (Rantelabi & Hernando, 2025) demonstrated that explainability techniques, such as SHAP-value interpretation in credit scoring, can improve the interpretability of algorithmic decisions in digital lending ecosystems. This insight supports the argument that explainable AI enhances trust by helping users understand, evaluate, and rely on AI-generated financial recommendations.

**Perceived Cybersecurity Assurance (PCSA):** Cybersecurity assurance reflects users' belief that adequate technological and organizational safeguards are in place to protect their data and transactions. Given the prevalence of cyber threats in digital financial services, perceived security has been shown to significantly shape trust and usage intentions (Al-Dosari et al., 2024; Rana et al., 2020). In AI-enabled banking, cybersecurity assurance is particularly important, as AI systems may expand the attack surface through increased data flows and system interconnectivity.

**Perceived AI Accuracy and Reliability (AIR):** Accuracy and reliability represent core functional attributes of AI systems. In the financial domain, errors or inconsistent recommendations can have severe consequences, undermining users' confidence in AI-generated outputs (Cao & Zhai, 2022; Lee et al., 2023). Empirical evidence suggests that AI accuracy and reliability perceptions are critical for building trust and fostering continued use (Bedué & Fritzsche, 2022; Dvoutely et al., 2025; Mfumbilwa et al., 2024).

**Perceived Privacy Protection (PPP):** PPP concerns users' perceptions of how AI-enabled services collect, store, and use their personal and financial data (Emuron et al., 2024). Prior studies highlight privacy as a key determinant of trust and technology use in digital financial services, particularly in emerging markets where regulatory awareness may vary (Odei-Appiah et al., 2022; Rana et al., 2020). Therefore, transparent and responsible data governance practices are expected to enhance trust and continuance intention (Abis et al., 2025; Ahsan et al., 2021).

**Digital Financial Literacy as a Moderating Factor:** While technological attributes play a crucial role in shaping trust and continued use, users' capabilities and knowledge also

matter (Egbeleo & Sodokin, 2025). Digital financial literacy refers to an individual's ability to understand and use digital financial services, evaluate financial information, and apply basic cybersecurity practices (Hussain et al., 2025). Prior research on the digital divide and fintech adoption suggests that users with higher levels of digital and financial literacy are better equipped to assess risks and benefits, leading to more sustained use (Goli et al., 2023; Odei-Appiah et al., 2022). Recent studies further indicate that user knowledge can moderate the relationship between trust and usage intention in AI contexts (Suryadi et al., 2025). Building on this insight, this study proposes that digital financial literacy strengthens the effect of trust on continuance intention, enabling users to translate trust into consistent usage of GenAI assistants in digital banking (Huang et al., 2023).

**Research gap and contributions:** Several gaps remain despite growing interest in AI adoption in banking. First, most existing studies focus on initial adoption rather than continued use of GenAI assistants. Second, prior research often examines isolated technological factors, overlooking their combined effects on trust and continuance intention. Third, the moderating role of digital financial literacy in AI-enabled banking contexts remains underexplored, particularly in emerging markets such as Vietnam.

Financial decision modeling also helps to contextualize the role of GenAI assistants in digital banking. Algorithmic models can support financial decisions, such as loan approval, by processing variables, including credit score and employment stability, as shown by (Mohammed & Mirlam, 2026). However, the behavioral value of such models depends on users' perceptions of transparency, reliability, and trust. Therefore, this study extends continuance research by examining how trustworthy AI attributes shape trust and sustained use in AI-enabled digital finance.

This study addresses these gaps by developing and empirically testing an integrated research model that examines how explainable AI, AI service quality, perceived cybersecurity assurance, perceived AI accuracy and reliability, and perceived privacy protection influence trust and continuance intention while considering the moderating role of digital financial literacy. This research offers novel insights into the sustainable adoption of generative AI in financial services by using a mixed-method approach and PLS-SEM analysis of data from 845 digital banking users in Vietnam. This study differs from prior AI continuance research in three ways. First, it focuses on generative AI assistants in digital banking, where AI outputs may directly affect users' financial decisions. Second, it integrates trust-related technological attributes, explainability, service quality, cybersecurity assurance, accuracy, reliability, and privacy protection within a single continuum. Third, it examines digital financial literacy as a boundary condition that explains when trust is more likely to translate into sustained use. These contributions extend AI continuance literature from general post-adoption behavior to the more risk-sensitive context of AI-enabled financial services. Based on the above theoretical foundations and empirical evidence, this study proposes the following hypotheses (H1–H12) in Figure 1.

H1: Explainable AI positively influences trust in digital banking generative AI assistants.

H2: AI service quality positively influences trust in digital banking generative AI assistants.

H3: Perceived cybersecurity assurance positively influences trust in digital banking generative AI assistants.

H4: Perceived AI accuracy and reliability positively influence trust in digital banking generative AI assistants.

H5: Perceived privacy protection positively influences trust in digital banking generative AI assistants.

H6: Explainable AI positively influences continuance intention to use AI assistants in digital banking.

H7: AI service quality positively influences continuance intention to use generative AI assistants in digital banking.

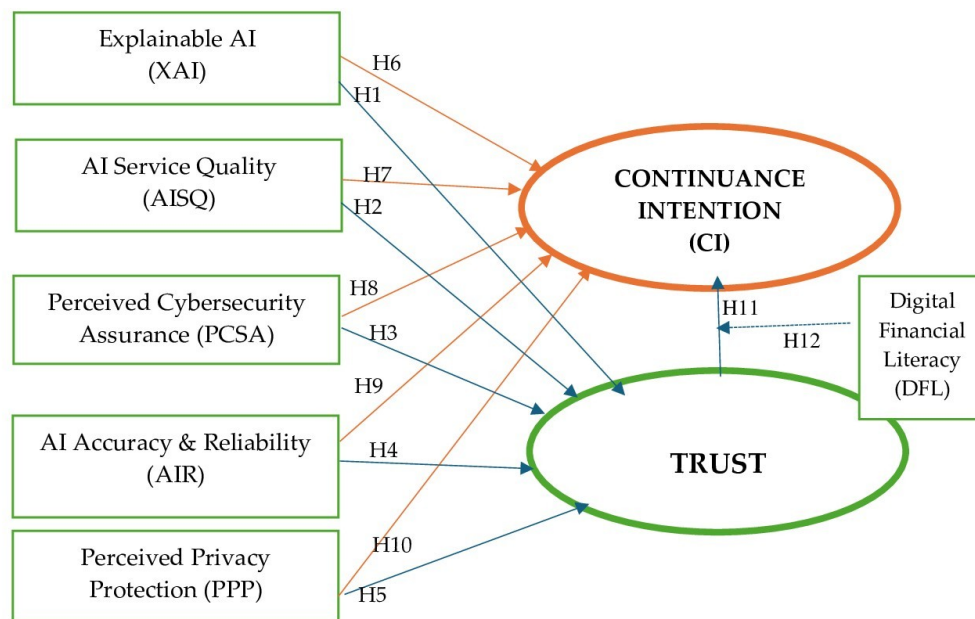
H8: Perceived cybersecurity assurance positively influences the intention to continue using generative AI assistants in digital banking.

H9: Perceived AI accuracy and reliability positively influence continuance intention to use generative AI assistants in digital banking.

H10: Perceived privacy protection positively influences continuance intention to use generative AI assistants in digital banking.

H11: Trust positively influences continuance intention to use generative artificial intelligence assistants in digital banking.

H12: Digital financial literacy positively moderates the relationship between trust and continuance intention, such that users with higher digital financial literacy have a stronger effect of trust on continuance intention.



**Figure 1** The model for critical factors affecting trust and continuance intention

Figure 1 illustrates the proposed research model, which examines the critical technological and behavioral factors influencing trust and continuance intention toward generative AI assistants in digital banking. The model integrates five key technology-related antecedents, namely, explainable AI, AI service quality, perceived cybersecurity assurance, perceived AI accuracy and reliability, and perceived privacy protection, reflecting the multifaceted nature of trustworthy AI in financial services.

The model positions trust as a central mediating mechanism through which technology characteristics shape users' continuance intention. In digital banking environments, trust denotes users' confidence that the AI-enabled service will perform reliably, transparently, and responsibly when handling sensitive financial information. By incorporating both direct paths from technological factors to continuance intention and indirect paths via trust, the model captures the dual role of technology in shaping sustained usage behavior. This structure acknowledges the technological attributes may directly influence continuance intention through perceived utility and performance, while others operate indirectly by fostering trust in AI-enabled banking services.

Furthermore, the model introduces digital financial literacy as a moderating variable in the relationship between trust and continuance intention. This moderation highlights the role of financial and digital capabilities in translating trust into sustained usage. Users with higher levels of digital financial literacy are better equipped to interpret AI-generated information, assess potential risks, and leverage digital banking services effectively, thereby strengthening the impact of trust on continuance intention. Finally, the proposed model provides a comprehensive and integrative framework for understanding the continued use of generative AI assistants in digital

banking. The model offers valuable theoretical insights and practical guidance for designing trustworthy AI systems and promoting the sustainable adoption of AI-driven banking services, particularly in emerging markets, by integrating perspectives on technological quality, security, privacy, trust, and user capability.

## 2. Methods

The research process includes 3 stages: the qualitative, preliminary, and official quantitative stages.



**Figure 2** The research process for critical factors affecting trust and continuance intention

Phase 1: The authors design a research model for five factors affecting trust and continuance intention, which is carried out through seven specific steps as follows:

**Step 1: Theoretical grounding and construct identification:** The research began with an extensive review of the literature on AI in financial services, digital banking, technology continuance, and trust in AI-enabled systems. The key constructs were identified based on prior studies on AI adoption, chatbot usage, digital financial services, and trustworthy AI, including explainable AI (XAI), AI service quality (AISQ), perceived cybersecurity assurance (PCSA), perceived AI accuracy and reliability (AIR), perceived privacy protection (PPP), trust, continuance intention, and digital financial literacy (DFL). This step ensured strong theoretical grounding and alignment with established research streams. The research model is grounded in TAM, ECM, and UTAUT. The TAM explains how perceived usefulness and system characteristics influence behavioral intention, the ECM provides a post-adoption perspective on continuance intention, and the UTAUT highlights the role of performance-related and user capability factors. Building on these theories, this study positions trust as the key mechanism through which trustworthy AI attributes shape continuance intention. The model also incorporates an AI governance perspective, as responsible AI adoption in banking requires transparency, accountability, fairness, cybersecurity, and data protection. Alyoubi and Alkhayat, 2025 emphasized that AI governance should address regulatory and ethical dimensions, which are highly relevant to GenAI assistants that process sensitive financial data and influence financial decisions.

**Step 2: Initial item generation:** Measurement items for each construct were adapted from validated scales reported in prior studies on AI services, chatbot adoption, digital banking, trust, and financial literacy. Items were carefully reworded to reflect the context of generative AI assistants in digital banking, ensuring conceptual consistency while maintaining content validity. All items were measured using a Likert-type scale ranging from “strongly disagree” to “strongly agree”.

**Step 3: Expert-based qualitative validation:** A qualitative phase was conducted involving 35 experts with extensive experience in digital banking, fintech, and AI-enabled financial services from Ho Chi Minh City and Dong Nai Province to refine the initial measurement instrument. Through structured group discussions and expert feedback sessions, participants evaluated each item’s relevance, clarity, and contextual appropriateness. This process eliminated ambiguous items, refined wording, and confirmed construct definitions.

**Step 4: Development of the official questionnaire:** The final version was developed based on expert feedback. The instrument was reviewed for clarity, logical flow, and consistency. A pilot review confirmed that the respondents could easily understand the items and complete the survey. This step resulted in a validated measurement instrument suitable for large-scale data collection.

**Step 5: Specific population and sampling strategy:** The specific population comprised customers who regularly use digital banking services and had prior experience interacting with AI-based assistants or chatbots embedded in banking applications. This focus ensured that respondents had sufficient exposure to generative AI assistants to provide informed evaluations.

In this study, a purposive convenience sampling approach was employed. Respondents were selected based on two screening criteria: regular users of digital banking services and prior experience interacting with AI-based assistants or chatbots embedded in banking applications. Because a complete sampling frame of GenAI-assisted digital banking users was not publicly available, probability-based random sampling was not feasible. Nevertheless, the study increased the diversity of the sample by distributing questionnaires through both online and in-person channels and screening respondents before data analysis.

**Step 6: Survey administration:** A total of 900 questionnaires were distributed via online and in-person methods to enhance diversity of responses. Data collection emphasized voluntary participation and anonymity according to ethical research standards. Respondents were screened to confirm regular digital banking service usage.

**Step 7: Data screening and validation:** After removing incomplete or inconsistent responses from the 900 distributed questionnaires, 845 valid responses were retained for analysis. The final sample size exceeded the minimum PLS-SEM requirements, providing adequate statistical power for hypothesis testing and moderation analysis.

**Step 8: Common method bias assessment:** Procedural remedies were applied during questionnaire design, including assuring respondent anonymity and minimizing item ambiguity. Statistical checks indicated no serious common method bias, indicating that the collected data were suitable for subsequent structural analysis.

**Step 9: Justification for PLS-SEM:** PLS-SEM was employed using SmartPLS 4.0. PLS-SEM was selected for its suitability for complex models involving multiple constructs, mediation, and moderation effects, as well as for its robustness in handling non-normal data distributions. Additionally, PLS-SEM is appropriate for predictive and exploratory research, aligning with the objectives of this study (Hair et al., 2019). The use of PLS-SEM is also consistent with applied data science approaches in banking research, where multivariate analytical techniques are commonly used to examine complex relationships among digital transformation, mediating mechanisms, and performance outcomes. For example, (Huy & Tam, 2025) demonstrated the relevance of applied data science methods for analyzing mediating effects in the Vietnamese banking context. This supports the suitability of PLS-SEM for testing the proposed model involving multiple antecedents, trust as a mediating mechanism, and digital financial literacy as a moderator.

**Step 10: Assessment of the measurement model:** The measurement model was evaluated by examining indicator reliability, internal consistency reliability, and convergent validity. Cronbach's alpha,  $\rho_a$  and  $\rho_c$  composite reliability, and average variance extracted (AVE) were assessed against established thresholds. All constructs demonstrated satisfactory reliability and convergent validity, indicating the robustness of the measurement model. Discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio of correlations. All HTMT values were below the recommended threshold, confirming adequate discriminant validity among the constructs.

**Step 11: Assessment of the structural model:** The structural model was evaluated by examining the path coefficients, coefficients of determination ( $R^2$ ), effect sizes ( $f^2$ ), and predictive relevance ( $Q^2$ ). The hypotheses were tested using a bootstrapping procedure with several resamples to ensure that the estimates of standard errors, t-values, and p-values were

stable. Both direct and indirect effects were assessed to examine trust's mediating role.

**Step 12: Moderation analysis:** An interaction term between trust and DFL was created using a two-stage approach in SmartPLS to test the moderating effect of DFL. The significance of the interaction effect was assessed using bootstrapping. A simple slope analysis was conducted to interpret the nature of the moderation effect, illustrating how varying levels of digital financial literacy influence the relationship between trust and continuance intention. This study ensures high methodological rigor in examining the continued use of generative AI assistants in digital banking by employing a structured three-stage, twelve-step methodology. The integration of expert-based qualitative validation with large-scale quantitative analysis provides strong empirical support for the proposed research model and enhances the findings' reliability, validity, and generalizability within emerging market contexts.

### 3. Results and Discussion

The demographic characteristics of the respondents are summarized to provide an overview of the sample profile and to assess the representativeness of Vietnamese digital banking users. The sample consists of 362 male respondents (42.8%) and 483 female respondents (57.2%). The higher proportion of female users suggests that women are actively engaging with digital banking services and AI-enabled applications, consistent with recent evidence indicating increasing female participation in DFS in emerging markets.

Regarding marital status, 61.9% of the respondents were married, while 38.1% were single. This distribution indicates that most users are individuals with family responsibilities, which may increase their reliance on convenient, efficient digital banking services, including generative AI assistants, to manage their financial activities. The sample is dominated by the 35–45 age group (52.5%), followed by 25–35 (23.7%), 45+ (15.5%), and 22–25 (8.3%). This age structure reflects a mature user base with substantial financial decision-making experience. Users in the 35–45 age group are typically economically active and more likely to value reliability, security, and service quality in digital banking platforms, reinforcing the relevance of trust-related constructs in this study.

A significant proportion of respondents reported high monthly income levels. Specifically, 37.4% earn more than 25 million VND per month, 35.4% earn between 20 and 25m VND, and only 5.0% earn less than 15 million VND per month. This income distribution suggests that the sample largely consists of financially capable users who frequent digital banking and are likely to interact with AI-based financial tools.

Finally, regarding usage experience, 36.3% of respondents have used digital banking services for 10–15 years and 36.1% for more than 15 years, whereas only 5.7% have less than 5 years of experience. This indicates that most respondents are experienced digital banking users, thereby strengthening the reliability of their evaluations of GAAs. The demographic profile confirms that the sample is well-suited to examining continuance intention toward AI-enabled digital banking services.

Table 1 shows the descriptive statistics and reliability assessment of the critical factors affecting trust and continuance intention toward generative AI assistants in digital banking. The table reports the means, standard deviations, Cronbach's alpha coefficients, composite reliability ( $\rho_c$ ), and average variance extracted (AVE) for all constructs in the research model. Overall, the results indicate satisfactory measurement properties and provide preliminary insights into respondents' perceptions of AI-enabled digital banking services.

From a descriptive perspective, the mean values of the constructs range from 3.093 to 3.313, indicating that respondents generally hold moderately positive perceptions of generative AI assistants and related technological attributes. Among all constructs, continuance intention (CI) recorded the highest mean value (mean = 3.313), followed closely by trust in generative AI assistants (TRUST) (mean = 3.305). This suggests that respondents intend to continue using generative AI assistants in digital banking and maintain a moderate level of trust in these systems on average. Such findings are reasonable given that most respondents are experienced

digital banking users with long-term exposure to technology-based financial services. In contrast, digital financial literacy (DFL) exhibits the lowest mean score (mean = 3.093), indicating that although users actively engaged with digital banking services, their perceived ability to fully understand and manage digital financial tools may remain limited.

**Table 1** Descriptive statistics and Cronbach's alpha for critical factors affecting the trust and continuance intention

| Items and Codes                           | Mean  | Std. Deviation | Cronbach's Alpha | Composite Reliability ( $\rho_c$ ) | AVE   |
|-------------------------------------------|-------|----------------|------------------|------------------------------------|-------|
| Explainable AI (XAI)                      | 3.172 | 0.953          | 0.945            | 0.960                              | 0.857 |
| AI Service Quality (AISQ)                 | 3.134 | 0.933          | 0.933            | 0.952                              | 0.832 |
| Perceived Cybersecurity Assurance (PCSA)  | 3.215 | 0.927          | 0.946            | 0.961                              | 0.861 |
| AI Accuracy and Reliability (AIR)         | 3.216 | 0.935          | 0.863            | 0.866                              | 0.631 |
| Perceived Privacy Protection (PPP)        | 3.125 | 0.938          | 0.935            | 0.953                              | 0.836 |
| Trust in Generative AI Assistants (TRUST) | 3.305 | 0.947          | 0.916            | 0.947                              | 0.856 |
| Continuance Intention (CI)                | 3.313 | 0.952          | 0.852            | 0.910                              | 0.771 |
| Digital Financial Literacy (DFL)          | 3.093 | 0.932          | 0.922            | 0.949                              | 0.862 |

Table 1 demonstrates strong internal consistency across all constructs from a reliability standpoint. Cronbach's alpha values range from 0.852 to 0.946, which is well above the recommended threshold of 0.70. Constructs such as perceived cybersecurity assurance (PCSA) ( $\alpha = 0.946$ ), explainable AI (XAI) ( $\alpha = 0.945$ ), and perceived privacy protection (PPP) ( $\alpha = 0.935$ ) exhibit exceptionally high reliability, indicating that the measurement items within each construct are highly consistent in capturing the intended latent concept.

Similarly, the composite reliability ( $\rho_c$ ) values for all constructs exceeded 0.866, further confirming the measurement model's robustness. The high composite reliability values suggest that the indicators collectively provide a reliable representation of their respective constructs, even in the presence of potential measurement error. In terms of convergent validity, all constructs reported AVE values above the recommended threshold of 0.50, ranging from 0.631 to 0.862. This indicates that each construct explains more than half of the observed indicators' variance. Although AI accuracy and reliability (AIR) recorded the lowest AVE (0.631) among the constructs, it still exceeded the minimum acceptable level, confirming adequate convergent validity. The slightly lower AVE may reflect the complexity of users' AI accuracy evaluations, as AI reliability perceptions can vary depending on specific interactions and outcomes.

The heterotrait–monotrait (HTMT) ratios used to assess discriminant validity among the study constructs were also evaluated (Table 2). All HTMT values were well below the conservative threshold of 0.85, indicating satisfactory discriminant validity. Even the highest correlations observed between AI service quality and trust (HTMT = 0.613) and between trust and continuance intention (HTMT = 0.575) remain within acceptable limits. These results confirm that the constructs are empirically distinct and that multicollinearity is not a concern, supporting the measurement model's robustness.

**Table 2** Discriminant validity assessment for trust and continuance intention

| Factors     | AIR   | AISQ  | CI    | DFL   | PCSA  | PPP   | TRUST | XAI   |
|-------------|-------|-------|-------|-------|-------|-------|-------|-------|
| AIR         | –     |       |       |       |       |       |       |       |
| AISQ        | 0.041 | –     |       |       |       |       |       |       |
| CI          | 0.106 | 0.545 | –     |       |       |       |       |       |
| DFL         | 0.158 | 0.140 | 0.081 | –     |       |       |       |       |
| PCSA        | 0.250 | 0.188 | 0.240 | 0.032 | –     |       |       |       |
| PPP         | 0.054 | 0.035 | 0.129 | 0.015 | 0.037 | –     |       |       |
| TRUST       | 0.118 | 0.613 | 0.575 | 0.077 | 0.176 | 0.078 | –     |       |
| XAI         | 0.050 | 0.033 | 0.137 | 0.114 | 0.137 | 0.033 | 0.094 | –     |
| DFL × TRUST | 0.108 | 0.023 | 0.070 | 0.066 | 0.105 | 0.114 | 0.075 | 0.074 |

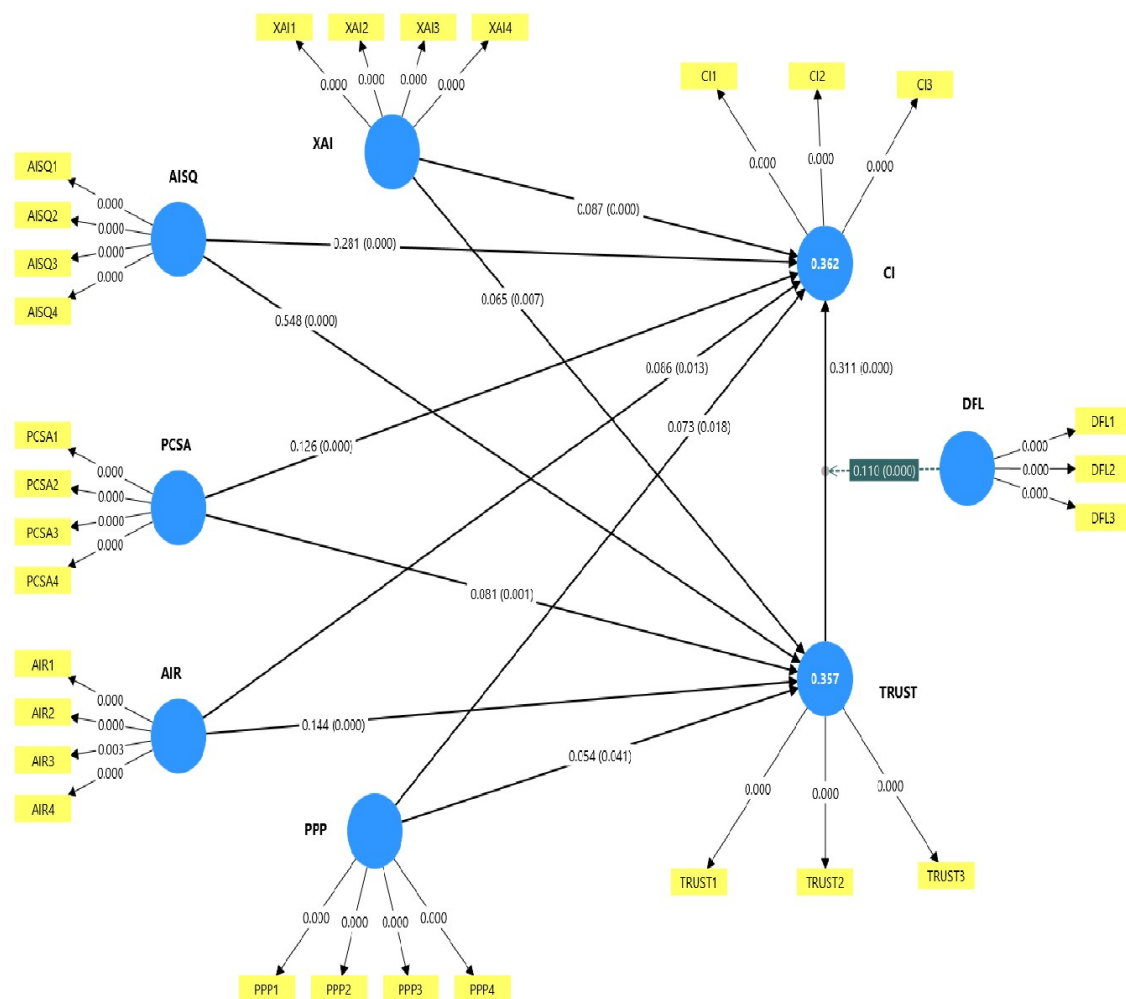
**Figure 3** Testing critical factors affecting the trust and continuance intention

Figure 3 shows the results of the structural model analysis examining the critical factors affecting trust and continuance intention toward generative AI assistants in digital banking. The model demonstrates moderate explanatory power, with  $R^2$  values of 0.357 and 0.362 for trust and 0.362 for continuance intention, indicating that the proposed technological factors jointly explain a substantial proportion of the variance in both constructs.

The results show that AI service quality exerts the strongest effect on trust ( $\beta = 0.548$ ,  $p < 0.001$ ), underscoring the central role of AI assistants' perceived performance, responsiveness,

and usefulness in fostering user trust. Other technological attributes, including AI accuracy and reliability ( $\beta = 0.144$ ,  $p < 0.001$ ), perceived cybersecurity assurance ( $\beta = 0.081$ ,  $p < 0.01$ ), explainable AI ( $\beta = 0.065$ ,  $p < 0.01$ ), and perceived privacy protection ( $\beta = 0.054$ ,  $p < 0.05$ ), also significantly contribute to trust formation, highlighting the multidimensional nature of trustworthy AI in digital banking.

Regarding continuance intention, trust emerged as the most influential predictor ( $\beta = 0.311$ ,  $p < 0.001$ ), followed by AI service quality ( $\beta = 0.281$ ,  $p < 0.001$ ). The remaining technological factors, perceived cybersecurity assurance, AI accuracy and reliability, explainable AI, and perceived privacy protection also exhibit significant direct effects on continuance intention, although with smaller magnitudes. This suggests that both functional performance and assurance-related factors play complementary roles in sustaining AI usage. Furthermore, Figure 3 reveals a significant moderating effect of digital financial literacy on the trust–continuance relationship ( $\beta = 0.110$ ,  $p < 0.001$ ). This finding indicates that users with higher levels of digital financial literacy are better able to translate trust into the continued use of AI assistants. Overall, the results provide strong empirical support for the proposed model and offer valuable insights into the sustainable adoption of AI-driven digital banking services.

**Table 3** Testing critical factors affecting the trust and continuance intention

| Relationships                       | Original Sample ( $\beta$ ) | Sample Mean | Std. Deviation | T Statistics | P Values |
|-------------------------------------|-----------------------------|-------------|----------------|--------------|----------|
| AIR $\rightarrow$ CI                | 0.086                       | 0.085       | 0.034          | 2.498        | 0.013    |
| AIR $\rightarrow$ TRUST             | 0.144                       | 0.148       | 0.036          | 4.057        | 0.000    |
| AISQ $\rightarrow$ CI               | 0.281                       | 0.280       | 0.035          | 8.132        | 0.000    |
| AISQ $\rightarrow$ TRUST            | 0.548                       | 0.549       | 0.031          | 17.917       | 0.000    |
| DFL $\times$ TRUST $\rightarrow$ CI | 0.110                       | 0.109       | 0.028          | 3.943        | 0.000    |
| PCSA $\rightarrow$ CI               | 0.126                       | 0.125       | 0.028          | 4.513        | 0.000    |
| PCSA $\rightarrow$ TRUST            | 0.081                       | 0.079       | 0.023          | 3.462        | 0.001    |
| PPP $\rightarrow$ CI                | 0.073                       | 0.075       | 0.031          | 2.375        | 0.018    |
| PPP $\rightarrow$ TRUST             | 0.054                       | 0.055       | 0.027          | 2.044        | 0.041    |
| TRUST $\rightarrow$ CI              | 0.311                       | 0.311       | 0.036          | 8.667        | 0.000    |
| XAI $\rightarrow$ CI                | 0.087                       | 0.089       | 0.025          | 3.551        | 0.000    |
| XAI $\rightarrow$ TRUST             | 0.065                       | 0.065       | 0.024          | 2.714        | 0.007    |

Table 3 shows the results of the structural model analysis examining the relationships among the critical technological factors, trust, and continuance intention toward generative AI assistants in digital banking. The analysis is based on the SmartPLS 4.0 bootstrapping procedure, with path coefficients ( $\beta$ ), t-statistics, and p-values used to assess the significance of the proposed hypotheses. Overall, all hypothesized relationships are statistically supported, demonstrating the robustness of the proposed research model.

**Effects of AI-related factors on trust:** The findings reveal that AI service quality (AISQ) has the strongest positive effect on trust ( $\beta = 0.548$ ,  $p < 0.001$ ). This result underscores the dominant role of generative AI assistants' perceived service performance, responsiveness, and usefulness in shaping users' trust in digital banking contexts. Users are more likely to perceive AI assistants as competent and dependable when they provide timely, accurate, and personalized responses, thereby strengthening trust. This finding aligns with prior research on AI-enabled customer service and chatbot adoption, which consistently highlights service quality as a primary antecedent of trust and sustained technology use.

In addition to AISQ, AI accuracy and reliability (AIR) exhibit a significant positive effect on trust ( $\beta = 0.144$ ,  $p < 0.001$ ). This suggests that users' confidence in the accuracy and consistency of AI-generated outputs is a critical component of trust formation. In financial services, where AI recommendations may influence monetary decisions, perceived reliability

becomes particularly salient. This result reinforces the argument that trustworthy AI systems must demonstrate not only advanced capabilities but also consistent and reliable performance.

Perceived cybersecurity assurance (PCSA) also significantly influences trust ( $\beta = 0.081$ ,  $p = 0.001$ ). Although the magnitude of this effect is smaller than that of AISQ and AIR, it remains statistically significant. This finding indicates that users' belief in the presence of effective security mechanisms, such as data protection, fraud prevention, and secure system architecture, contributes to trust in generative AI assistants. Cybersecurity assurance acts as a foundational condition for trust in digital banking environments characterized by heightened cyber risks, even if it is not the most visible driver.

Similarly, explainable AI (XAI) positively affects trust ( $\beta = 0.065$ ,  $p = 0.007$ ). This result highlights the importance of transparency and interpretability in AI systems. Users are more likely to trust the system when they understand how AI assistants generate recommendations or responses, particularly in complex financial decision-making scenarios. Although the effect size is modest, the significance of XAI underscores its role in enabling trustworthy AI deployment.

Finally, perceived privacy protection (PPP) exerts a significant but comparatively weaker effect on trust ( $\beta = 0.054$ ,  $p = 0.041$ ). This suggests that while users value privacy protection, its influence on trust may be less pronounced than that of performance- and security-related factors. One possible explanation is that users often take privacy protection for granted or assume that banks already comply with data protection regulations. Nonetheless, the significance of PPP underscores that responsible data governance remains essential to trust in AI-enabled banking services.

**Direct effects on continuance intention:** Turning to continuance intention (CI), the results demonstrate that trust is the most influential predictor ( $\beta = 0.311$ ,  $p < 0.001$ ). This finding provides strong empirical support for the central role of trust in sustaining the long-term use of generative AI assistants. Trust reduces the perceived uncertainty and risk associated with AI-driven services, thereby encouraging users to engage with these technologies over time. This result is consistent with established theories of technology continuance, which emphasize trust as a key determinant of post-adoption behavior.

AI service quality (AISQ) has a strong direct effect on continuance intention ( $\beta = 0.281$ ,  $p < 0.001$ ), nearly as large as the effect of trust. This indicates that users' decisions to continue using generative AI assistants are strongly shaped by their ongoing service experiences. Poor service quality may discourage continued use even in the presence of trust, highlighting the dual importance of functional performance and psychological assurance.

The remaining technological factors, perceived cybersecurity assurance (PCSA) ( $\beta = 0.126$ ,  $p < 0.001$ ), AI accuracy and reliability (AIR) ( $\beta = 0.086$ ,  $p = 0.013$ ), explainable AI (XAI) ( $\beta = 0.087$ ,  $p < 0.001$ ), and perceived privacy protection (PPP) ( $\beta = 0.073$ ,  $p = 0.018$ ) also have significant direct effects on continuance intention. Although these effects are smaller in magnitude, they collectively demonstrate that users evaluate multiple dimensions of AI systems when deciding whether to continue using them. Specifically, assurance-related factors, such as security and privacy, complement performance-related attributes by reducing perceived risk and enhancing confidence in long-term use.

**Mediating role of trust:** The simultaneous significance of direct effects (from technological factors to CI) and indirect effects via trust suggests that trust partially mediates the research model. For instance, AISQ influences continuance intention both directly and indirectly through trust, indicating that high-quality AI services not only enhance trust but also provide immediate functional value that motivates continued use. Similarly, AIR, PCSA, XAI, and PPP contribute to continuance intention by strengthening trust and exerting independent effects. This pattern highlights the multifaceted pathways through which technological attributes shape sustained AI usage behavior.

**Moderating effect of digital financial literacy (DFL):** A key contribution of this study lies in the examination of DFL as a moderating variable. The interaction effect between trust and DFL is positive and significant ( $\beta = 0.110$ ,  $p < 0.001$ ), indicating that DFL strength-

ens the relationship between trust and continuance intention. This result implies that users with higher levels of financial and digital knowledge are better able to translate trust into consistent usage behavior. Such users may possess greater confidence in interpreting AI-generated financial information, assessing risks, and leveraging advanced digital banking features, thereby amplifying the impact of trust on continuance intention. This finding extends prior research by demonstrating that trust alone may not be sufficient to ensure sustained use of generative AI assistants; rather, user capability plays a critical enabling role. In emerging markets such as Vietnam, where digital financial literacy levels vary widely, this moderating effect offers valuable insights into how banks can promote sustainable AI adoption.

**Overall implications of the structural results:** The results presented in Table 3 provide strong empirical support for the proposed research model. The findings confirm that a combination of technological performance, assurance mechanisms, trust, and user capabilities drives the continued use of generative AI assistants in digital banking. AI service quality and trust are the most influential factors, while cybersecurity, privacy, explainability, and accuracy serve as complementary drivers that enhance confidence and reduce perceived risk. The significant moderating role of digital financial literacy further highlights the importance of user education and capability development in realizing the full potential of AI-enabled digital banking services. Finally, Table 3 demonstrates that the proposed model offers a comprehensive and empirically validated explanation of trust formation and continuance intention in the context of generative AI assistants, providing a solid foundation for theoretical advancement and practical decision-making in digital banking.

### 3.1 Discussion of the findings

This study investigated the critical technological and behavioral factors influencing trust and continuance intention toward generative artificial intelligence (AI) assistants in digital banking, with a particular focus on the moderating role of digital financial literacy in an emerging market context. The empirical findings provide several important insights that both confirm and extend the existing literature on AI-enabled financial services.

**The central role of AI service quality:** AI service quality (AISQ) emerges as the strongest predictor of trust and a major direct determinant of continuance intention. This result underscores that users primarily evaluate generative AI assistants based on their functional performance, responsiveness, usefulness, and ability to provide accurate and timely financial support. This finding is consistent with prior studies on AI-based chatbots and digital service systems, which emphasize service quality as a key driver of trust and sustained usage (Adam et al., 2021; Dawar et al., 2022; Mfumbilwa et al., 2024). High AI service quality signals technological competence and organizational reliability in the context of digital banking, thereby reducing users' uncertainty and perceived risk. Although generative AI introduces advanced capabilities, such as natural language generation and personalized responses, users ultimately assess its value through everyday service encounters. This reinforces the argument that technological sophistication alone is insufficient to ensure sustainable AI adoption; instead, consistent service performance remains fundamental (Joshi et al., 2025; Lee et al., 2023).

**Trust as a pivotal mechanism for continuance intention:** The findings confirm that trust is the most influential determinant of continuance intention, supporting the central premise of post-adoption and technology continuance theories. Trust significantly enhances users' willingness to continue using generative AI assistants, underscoring its role as a psychological mechanism that mitigates perceived uncertainty in AI-driven decision-making (Ajzen, 2020; Lee et al., 2023). This result aligns with recent empirical evidence in AI-enabled banking contexts, demonstrating that trust reduces perceived vulnerability and strengthens long-term engagement with AI systems (Queiroz et al., 2024; Zhou et al., 2022). Importantly, this study conceptualizes trust at the system and service level, rather than as interpersonal trust, addressing concerns raised by scholars who caution against anthropomorphizing trust in human-AI relationships (KrÄijger and Wilson 2023; Al, 2023). The findings offer a pragmatic, con-

textually grounded understanding of trust in generative AI applications by focusing on trust in AI-enabled banking services.

These findings are consistent with recent high-impact studies showing that the use of generative AI is shaped not only by perceived usefulness and system performance but also by users' capability, trust, and contextual safeguards. For example, recent GenAI research using PLS-SEM and fsQCA demonstrated that generative AI can generate both benefits and risks, depending on users' knowledge, motivation, and interaction quality. Similarly, recent evidence on ChatGPT adoption shows that intention and actual use are influenced by performance-related factors and moderated by contextual norms and user capabilities. Consistent with these studies, the present findings suggest that the continuance of GenAI assistants in banking depends on both technological quality and users' ability to interpret and manage AI-enabled services (Shahzad et al., 2025a).

**The role of AI accuracy, cybersecurity, privacy, and explainability:** Beyond service quality, the results reveal that AI accuracy and reliability, perceived cybersecurity assurance, perceived privacy protection, and explainable AI significantly contribute to trust and continuance intention, albeit with smaller effect sizes. These findings highlight the multidimensional nature of trustworthy AI in financial services. Perceived AI accuracy and reliability play a crucial role in trust formation, reflecting users' concerns about the accuracy and consistency of AI-generated financial information. This finding supports prior research emphasizing that unreliable or inconsistent AI outputs, particularly in high-stakes financial contexts, can quickly erode trust (Bedué & Fritzsche, 2022; Cao & Zhai, 2022). Similarly, cybersecurity assurance significantly influences both trust and continuance intention. Users are highly attentive to security-related issues, including fraud prevention and data protection mechanisms, given the sensitivity of financial data. This result is consistent with studies highlighting cybersecurity as a foundational condition for the adoption of digital financial services in emerging economies (Al-Dosari et al., 2024; Rana et al., 2020).

Perceived privacy protection also positively affects trust and continuance intention, although its impact is comparatively weaker. One plausible explanation is that when interacting with established banking institutions, users may assume a baseline level of privacy protection, thereby reducing the salience of privacy concerns unless breaches occur. Nevertheless, the importance of privacy protection underscores the need for transparent data governance practices in AI-enabled banking (Butler et al., 2023; Odei-Appiah et al., 2022). Finally, by enhancing transparency and user understanding, explainable AI contributes to trust and continued use. Although the effect size is modest, the importance of explainability indicates that users value insights into how AI systems generate recommendations, particularly in complex financial decision-making scenarios. This finding aligns with calls for greater transparency and accountability in AI systems to foster user confidence (Bedué & Fritzsche, 2022; Choung et al., 2023).

**Partial mediation of trust:** The simultaneous significance of both direct and indirect effects suggests that trust partially mediates the relationship between technological factors and continuance intention. This implies that technological attributes influence continued use by enhancing trust and delivering immediate functional value. For example, AI service quality and cybersecurity assurance directly encourage continued use by improving user experience and reducing perceived risk and indirectly strengthen continuance intention through trust. This nuanced mediation pattern extends prior research by demonstrating that trust is a critical, but not exclusive, pathway to sustained AI usage. Users may continue to use generative AI assistants even as trust is developing, if the perceived benefits outweigh the perceived risks. This insight contributes to a more refined understanding of AI-enabled digital services' post-adoption behavior (Lee et al., 2023).

**Moderating role of digital financial literacy (DFL):** One of the most significant contributions of this study is its identification of DFL as a moderator in the trust–continuance relationship. Higher levels of digital financial literacy strengthen the effect of trust on continuance intention. This finding suggests that users with greater financial and digital knowledge

are better equipped to interpret AI-generated outputs, assess risks, and use advanced digital banking functionalities. This result is consistent with research on the digital divide and fintech adoption, which emphasizes that user capabilities shape how individuals engage with and benefit from digital financial services (Hussain et al., 2025; Odei-Appiah et al., 2022). Moreover, it extends recent studies on AI adoption by empirically demonstrating that user knowledge amplifies trust's behavioral impact (Suryadi et al., 2025). In emerging markets such as Vietnam, where digital financial literacy levels vary widely, this moderating effect underscores the importance of user education in achieving sustainable AI adoption. From a measurement perspective, digital financial literacy should not be treated merely as general financial knowledge. In AI-enabled banking, users' ability to understand digital financial services, recognize cybersecurity risks, evaluate AI-generated financial information, and make informed decisions should be captured without excessive reliance on automated recommendations. Therefore, future DFL measurement in GenAI banking contexts should combine financial knowledge, digital operation skills, privacy awareness, and AI-related risk evaluation. This broader operationalization can improve the validity of DFL scales in AI-driven financial services studies.

**Contextual contributions and implications for emerging markets:** This study contributes context-specific insights to the broader literature on AI-enabled banking in emerging economies by focusing on Vietnam. The findings suggest that while users in emerging markets increasingly embrace generative AI assistants, sustained use depends on a delicate balance between technological performance, trust, and user capability. This complements existing research highlighting the role of institutional quality, digital infrastructure, and financial literacy in shaping DFS outcomes (Kshetri, 2021; Mhlanga & Mhlanga, 2020). Finally, the discussion demonstrates that the sustainable adoption of generative AI assistants in digital banking requires more than advanced algorithms. A holistic approach that combines high-quality AI services, robust security and privacy safeguards, transparent and explainable systems, and continuous investment in users' digital financial literacy is required.

Recent GenAI and ICT adoption studies support the relevance of capability-based and context-sensitive models. (Shahzad et al., 2025b) demonstrated that GenAI outcomes depend on interaction quality, knowledge acquisition, and user-related conditions. (Subhani et al., 2025) confirmed that the adoption and actual use of ChatGPT are influenced by performance expectancy, self-efficacy, and moderating contextual factors. (Shahzad et al., 2025a) also demonstrated that using PLS-SEM, technology self-efficacy and task-technology fit are important in explaining the intention to use ICT. These studies reinforce the importance of integrating technological quality, trust, and user capability in the proposed model.

The moderating role of digital financial literacy indicates that user competence is a critical condition for transforming trust into sustained use. Users with higher digital financial literacy are more capable of understanding AI-generated financial information, evaluating potential risks, and using digital banking functions effectively. Therefore, trust alone may not be sufficient to ensure continuance intention; users also need cognitive and operational capabilities to interact confidently with AI-enabled banking systems. This finding is consistent with workplace and performance-related technology adoption perspectives, which suggest that when users possess adequate digital competence, technology produces stronger behavioral and performance outcomes. For example, (Hien & Tam, 2025) showed that the use of technology in Vietnamese commercial banks is closely associated with user capability and performance-related outcomes. Digital financial literacy plays a similar enabling role by strengthening the behavioral impact of trust on continuance intention.

### 3.2 Policy Recommendations

Based on the standardized path coefficients ( $\beta$ ) obtained from the structural model, this study proposes a set of policy recommendations that are prioritized according to the relative strength of each determinant affecting trust and continuance intention toward generative AI assistants in digital banking. These recommendations provide a clear, evidence-based roadmap for

policymakers, regulators, and banking institutions seeking to promote the sustainable adoption of generative AI technologies by grounding policy implications in empirical effect sizes rather than abstract considerations. Policy recommendations should be prioritized according to the findings' empirical strength. First, banks should improve AI service quality by ensuring responsiveness, contextual relevance, accuracy, and seamless integration with existing digital banking platforms. Second, trust should be institutionalized through transparent AI governance, clear responsibility for AI-generated outputs, user redress mechanisms, and AI limitation communication. Third, policymakers and banks should invest in digital financial literacy programs that cover AI-enabled financial services, cybersecurity awareness, privacy protection, and responsible use of AI recommendations. Fourth, cybersecurity, privacy, accuracy, and explainability standards should be embedded into AI banking systems through regular audits, human oversight for high-risk decisions, and user-friendly explanations. Together, these measures can strengthen user trust, reduce perceived risk, and promote GenAI assistants' sustainable continuance in digital banking.

(1) **Enhancing AI Service Quality:** Policymakers and banking regulators should encourage financial institutions to prioritize service performance benchmarks for AI-enabled banking services. This includes ensuring high responsiveness, accuracy of AI-generated responses, contextual relevance, and seamless integration with existing banking platforms. Regulatory bodies may consider issuing AI service quality guidelines that define minimum performance standards for generative AI assistants deployed in banking environments. Such guidelines could include requirements for response accuracy thresholds, system uptime, and monitoring of customer satisfaction. In addition, regulators should promote continuous AI system auditing and performance evaluation to ensure that service quality remains consistent as models are updated or retrained. Banks should invest in robust AI infrastructure, human-AI collaboration mechanisms, and ongoing training for AI development teams from an institutional perspective. High-quality AI services not only improve user experience but also directly strengthen trust and sustained usage, making them the most impactful and cost-effective policy lever.

(2) **Strengthening Trust as a Core Governance Objective:** Therefore, trust should be treated as a core governance objective, rather than an implicit technological deployment outcome. Policymakers should promote trust-by-design frameworks for AI in banking, encouraging institutions to embed ethical, transparent, and user-centric principles throughout the AI lifecycle. Regulatory guidance should emphasize accountability mechanisms, such as clearly defined responsibility for AI-generated decisions and accessible customer redress channels. In turn, banks should communicate trust-enhancing practices more explicitly to users. This includes transparent disclosure of AI usage, clear explanations of AI limitations, and proactive communication regarding data protection and security measures. By institutionalizing trust as a strategic goal, regulators and banks can significantly improve users' willingness to continue using generative AI assistants.

(3) **Advancing Digital Financial Literacy:** Consequently, policies aimed at enhancing digital financial literacy should be considered a high-impact, long-term investment. Governments and central banks should integrate digital financial literacy programs into national financial inclusion and digital transformation strategies. These programs should go beyond basic financial education to include AI-enabled financial services, algorithmic decision-making, cybersecurity awareness, and responsible use of digital banking tools. Banks can complement public initiatives by offering in-app educational features, such as interactive tutorials, AI explanation dashboards, and group with ML. Improving digital financial literacy not only amplifies the behavioral impact of trust but also reduces misuse, misunderstanding, and overreliance on AI-generated outputs.

(4) **Ensuring Robust Cybersecurity Assurance:** Perceived cybersecurity assurance significantly influences both trust and continuance intention, highlighting the importance of secure AI deployment in digital banking. To address the vulnerabilities introduced by large-scale data processing and interconnected AI systems, policymakers should strengthen cybersecurity regulations specific to AI-enabled financial services. Regulatory authorities may mandate pe-

riodic cybersecurity stress testing and AI-specific risk assessments to ensure that new attack surfaces are not introduced by generative AI assistants. Clear incident reporting requirements and penalties for data breaches can further reinforce institutional accountability. At the organizational level, banks should adopt advanced security measures, including encryption, anomaly detection, and real-time monitoring, while clearly communicating these measures to users. Institutions can directly increase user confidence and sustained engagement with AI-enabled banking services by enhancing perceived cybersecurity assurance. Given Vietnam's growing cybersecurity threats, ensuring robust protection for GenAI systems in banking is a top priority. Banks should invest in advanced cybersecurity infrastructure, including real-time monitoring, regular penetration testing, and AI-specific security assessments. From a policy perspective, regulators may require banks to conduct dedicated cybersecurity risk assessments of AI-enabled systems and to publicly communicate their security commitments to customers. Clear communication of security measures can significantly enhance the perceived cybersecurity assurance and confidence of users in AI-driven digital banking.

**(5) Improving AI Accuracy and Reliability:** AI accuracy and reliability are essential for building trust and encouraging continued use, particularly in high-stakes financial contexts. Policymakers should encourage the adoption of model validation and reliability standards for banking generative AI applications. When AI confidence is low, these standards may include requirements for regular performance testing, bias detection, and fallback mechanisms. Banks should implement human-in-the-loop systems that allow human oversight for complex or high-risk transactions. Institutions can mitigate user skepticism and reinforce trust by ensuring that AI-generated outputs are consistently accurate and reliable. Accuracy and reliability are essential for adopting generative AI in Vietnam's financial sector, where users are cautious about AI-generated financial advice. Banks should implement human-in-the-loop mechanisms, particularly for high-risk transactions or complex financial recommendations. To maintain reliability, regular performance audits and continuous model retraining using locally relevant data are also necessary. Policymakers may encourage independent validation of AI systems in banking to reduce errors, improve consistency, and reinforce trust in AI-assisted financial services.

**(6) Promoting Explainable AI:** Although explainable AI has a smaller effect size than service quality and trust, its significance highlights the importance of transparency in AI governance. Policymakers should support the adoption of explainability requirements for AI systems used in financial services, particularly when AI outputs influence financial decisions. Regulators may issue guidance on minimum explainability standards, such as requiring AI systems to provide users with understandable reasons for their recommendations or decisions. Banks can operationalize these requirements by integrating user-friendly explanation interfaces and visualizations within digital banking applications. Explainable AI not only enhances trust but also supports informed user decision-making, aligning with the broader goals of consumer protection and responsible AI use. In Vietnam, many users are still unfamiliar with complex AI systems. Therefore, explainability plays an important role in enhancing the acceptance of generative AI assistants. Banks should develop user-friendly explanation interfaces that clearly communicate the rationale for specific recommendations or alerts. Authorities may promote transparency standards for AI in the banking sector, particularly for AI functions that influence financial decisions, from a regulatory standpoint. Improved explainability can reduce information asymmetry between users and AI systems and support more informed decision-making.

**(7) Strengthening Privacy Protection Frameworks:** Although perceived privacy protection has smaller effect sizes, it remains a significant determinant of trust and continuance intention. Policymakers should continue to reinforce data protection regulations and ensure their effective enforcement in the context of AI-enabled banking. Banks should adopt transparent data governance practices that clearly inform users about data collection, storage, and use. Privacy-by-design principles should be embedded in artificial intelligence systems to minimize unnecessary data processing and enhance user confidence. Taken together, these policy recommendations suggest that a hierarchically structured policy approach is required for the sus-

tainable adoption of generative AI assistants in digital banking. Immediate priority should be given to improving AI service quality and institutionalizing trust, followed by long-term investments in digital financial literacy and robust cybersecurity governance. Complementary policies addressing AI accuracy, explainability, and privacy protection further reinforce user confidence and sustained usage. By aligning policy priorities with empirically validated effect sizes, policymakers and banking institutions can allocate resources and maximize the societal and economic benefits of generative AI in digital banking, particularly in countries such as Vietnam.

#### 4. Conclusions

This study examined the critical factors influencing trust and continuance intention toward generative AI assistants in digital banking, with particular attention to the moderating role of digital financial literacy in an emerging market context. Employing a mixed-method research design, the study combined expert-based qualitative validation with large-scale quantitative analysis using PLS-SEM on data collected from 845 digital banking users in Vietnam. The findings demonstrate that both technological performance and assurance-related factors play significant roles in shaping users' trust and continued use of generative AI assistants. Among the examined antecedents, AI service quality emerged as the most influential driver of trust and a major determinant of continuance intention, underscoring the importance of reliable, responsive, and useful AI-enabled services. Trust was identified as a central mechanism that strongly enhances users' intention to continue using generative AI assistants and partially mediates the effects of key technological attributes. In addition, factors such as AI accuracy and reliability, perceived cybersecurity assurance, explainable AI, and perceived privacy protection significantly contributed to trust formation and sustained usage behavior. Importantly, the study reveals that digital financial literacy strengthens the relationship between trust and continuance intention, indicating that users with higher financial and digital competencies are better able to translate trust into long-term engagement with AI-enabled banking services. This insight highlights the critical role of user capability in achieving sustainable AI adoption. Finally, this research advances understanding of the adoption of trustworthy generative AI in digital banking by offering an integrative framework that captures the interplay among technology characteristics, trust, and user capabilities. The findings provide a solid empirical foundation for both academic inquiry and practical decision-making in the design and governance of AI-driven financial services.

**Limitations and future research:** Despite its theoretical and empirical contributions, this study has several limitations that should be acknowledged and addressed in future research. First, the study employs a cross-sectional research design, which captures users' perceptions and behavioral intentions at a single time point. Although this approach is suitable for examining relationships among constructs, it does not permit causal inference or the examination of changes in trust and continuance intention over time. Future studies may adopt longitudinal designs to examine how users' trust in generative AI assistants evolves over time and in response to technological advancements. Second, the empirical analysis is conducted in Vietnam, an emerging market with unique institutional, technological, and cultural characteristics. Although this context offers valuable insights, the findings may be limited in their generalizability to other countries or regions. To enhance external validity, future research could replicate the proposed model in different institutional settings, including developed economies or cross-country comparative studies. Third, this study focuses on a selected set of technological and behavioral factors. Other potentially relevant variables, such as technology anxiety, perceived ethical risk, algorithmic bias, and emotional attachment to AI systems, were not incorporated into the model. Future research could extend the framework by integrating these constructs to provide a more comprehensive understanding of AI continuance behavior. Finally, this study relies on self-reported survey data, which may be subject to common-method bias or social desirability effects despite the implementation of procedural and statistical remedies. Future studies could complement survey data with objective usage data, experimental designs, or quali-

tative approaches to triangulate findings and deepen insights into user–AI interactions in digital banking.

Overall, these future research directions would further strengthen the theoretical positioning, methodological transparency, and critical understanding of GenAI continuance in digital banking. Future studies can provide deeper insights into how trust, AI governance, and user capability jointly shape the sustainable adoption of AI-enabled financial services by combining stronger theoretical grounding, more rigorous validation procedures, and behavioral usage data.

### Acknowledgements

The authors thank the managers, customers, and the rector of Lac Hong University (LHU), Grant Number: 651/QD-DHLH, 21/4/2026, Dong Nai City, Vietnam.

### Author Contributions

The authors contributed equally to conceptualization, investigation, methodology, data analysis, and original draft.

### Conflict of Interest

No potential conflict of interest was reported by the author.

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