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AI-Based Financial Literacy, Perceived Ease of Use, Technology Readiness, and Personal Financial Management Behavior: the Mediating Role of Trust in AI

Jamal Hanaffy¹, Dewi Listiorini², Hendri Sukma³

¹²Universitas Mitra Bangsa, Jakarta, Indonesia, ³Universitas Pancasila, Jakarta, Indonesia

Correspondence: hanaffyjamal@gmail.com¹

Abstract

Advances in artificial intelligence (AI) have transformed personal financial management, yet the gap between the adoption of digital financial tools and the financial literacy and trust required for effective use remains underexplored, particularly in urban Indonesia. This study examines the effects of AI-Based Financial Literacy, Perceived Ease of Use, and Technology Readiness on Personal Financial Management Behavior, with Trust in AI as a mediating variable. The study extends the Technology Acceptance Model (TAM) and Technology Readiness Index (TRI) through the Stimulus-Organism-Response (S-O-R) framework by integrating trust into an AI-based financial behavior model. A quantitative explanatory design was employed using survey data from 200 purposively selected respondents in Depok City, aged 18–40 years and using AI-based financial applications. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. The results show that AI-Based Financial Literacy ($\beta = 0.214$; $p = 0.001$), Perceived Ease of Use ($\beta = 0.187$; $p = 0.005$), and Technology Readiness ($\beta = 0.168$; $p = 0.008$) positively and significantly affect Personal Financial Management Behavior. All hypotheses (H1–H6) were supported, with $R^2 = 0.612$. The findings confirm that Trust in AI mediates these relationships. The study contributes to TAM and TRI by highlighting trust as a mechanism linking AI-related capabilities to financial behavior and offers implications for developing an inclusive and trustworthy digital financial ecosystem.

KEYWORDS

AI-based financial literacy; perceived ease of use; technology readiness; trust in AI; personal financial management behavior.

Introduction

The emergence of artificial intelligence (AI) has fundamentally altered the realm of personal financial management, and Indonesia is no exception. This shift is particularly evident in the swift adoption of financial technology (fintech) in metropolitan regions such as Depok City. As an integral part of the Jabodetabek area, Depok benefits from the nation's most developed and sophisticated information and communications technology (ICT) infrastructure (Meilasari-Sugiana et al., 2023). The characteristics of Depok's society, integrated into the Jabodetabek digital ecosystem, make this area a representative setting for studying financial technology adoption, where socio-economic status is not the main determinant of fintech use, but rather psychological factors such as perceived control and the availability of service options (Meilasari-Sugiana et al., 2023). Studies on Personal Financial Management (PFM) among Generation Z in the Jabodetabek area, including Depok, show that Perceived Ease of Use significantly influences the intention to use financial management applications, along with attitude, perceived behavioral control, perceived cost, and compatibility (Akira, 2020).

According to the 2024 National Survey of Financial Literacy and Inclusion (SNLIK)

released by Indonesia's Financial Services Authority (OJK), the national financial literacy index stands at only 65.43%, with considerably lower rate documented among younger demographics (Hikmah, 2024). Although the lowest recorded score (51.70%) pertains to individuals aged 15–17, this finding holds direct relevance to our 18–40 target population. Extrapolation is empirically justified on two grounds: first, financial literacy and management behaviors are substantially shaped during late adolescence and tend to persist into early adulthood without targeted intervention (Lusardi, 2019; Lusardi & Mitchell, 2014); second, the 15–17 cohort constitutes the immediate pipeline entering our sampled age bracket, meaning that their literacy deficits directly foreshadow the knowledge constraints faced by emerging adults in Depok City. This justification is further reinforced by recent OJK supplementary reports indicating that financial literacy among Indonesian millennials and Gen Z (aged 18–40) remains notably below the national average, particularly in urban contexts where digital financial products proliferate rapidly (OJK, 2024). Collectively, these empirical and theoretical rationales establish a robust linkage between the cited adolescent literacy gap and the behavioral challenges confronting our target demographic, thereby underscoring the urgency of investigating AI-driven financial literacy and trust mechanisms among the 18–40 urban population. It underscores the urgency of a more comprehensive understanding of the factors influencing personal financial management behavior in the digital era. Recent cross-country studies confirm that attitudes toward AI in personal financial planning are still evolving and vary significantly across demographic groups (D'Acunto & Rossi, 2022; Waliszewski & Warchlewska, 2020).

Previous studies in Depok and its surrounding areas show that mobile banking technology positively affects customer satisfaction, with perceived ease of use being a key factor in the adoption of digital financial services (Rahayu et al., 2024). Studies on mobile banking usage in the Jakarta, Bogor, Depok, Tangerang, and Bekasi (Jabodetabek) area confirm that perceived usefulness and perceived credibility significantly influence the decision to use mobile banking. However, perceived ease of use was found to have no significant effect in the context of Islamic banking (Aqilah & Fathoni, 2023), suggesting that the role of ease of use may vary across different financial service contexts and user segments. Meanwhile, research on millennials in Greater Jakarta found that psychological factors, such as feeling in control and the availability of service options, are important determinants of fintech adoption (Meilasari-Sugiana et al., 2023). From an international perspective, the adoption of intelligent virtual assistants in financial services is strongly influenced by anthropomorphic and socio-psychological factors, including perceived ease of use (Priya & Sharma, 2023). Furthermore, machine learning models are increasingly used for predictive analytics in personal finance, enhancing the relevance of AI-based financial literacy (Kalai et al., 2022). These studies collectively suggest that while technological attributes and user perceptions are important, their influence on financial behavior is likely mediated by psychological mechanisms such as trust, which has not been comprehensively tested in an integrated framework within the Indonesian urban context.

This study contributes to the existing literature by examining an integrative model that connects AI-based financial literacy, perceived ease of use, and technology readiness through the mediating role of Trust in AI in explaining personal financial management behavior among urban AI-fintech users in Indonesia. Although previous studies have examined trust in AI adoption (Chang, 2026; Maier et al., 2022), financial literacy (Novianti & Retnasih, 2023), and technology acceptance using TAM or TRI independently (Priantinah et al., 2019; Saputri, 2024), the integration of AI-specific financial literacy, TAM, TRI, and the S-O-R framework through Trust in AI remains relatively underexplored, particularly in the context of AI-enabled personal financial management in Indonesian metropolitan areas.

Table 1, summarizes the closest prior studies and highlights how the present study differs regarding theoretical integration, AI-specific literacy, mediation mechanism, study population, and research setting.

The closest prior studies, such as Sebayang et al. (2024), examined trust and PEOU as direct predictors of mobile banking adoption without considering AI-specific literacy or the mediating role of trust, while Novianti & Retnasih (2023) tested financial literacy and fintech access with locus of control as a moderator but did not incorporate trust as a mediator. Furthermore, this study extends the theoretical integration of TAM and TRI by embedding them within the stimulus-organism-response (S-O-R) paradigm (Mehrabian & Russell, 1974), wherein technological and knowledge-related factors act as stimuli that influence the organismic state of trust, which subsequently drives behavioral responses. This tripartite integration—linking TAM, TRI, and S-O-R through trust mediation—has not been empirically tested in developing-country metropolitan contexts, thereby addressing a theoretically grounded gap in the literature on AI-driven financial behavior. Recent evidence suggests that trust in AI-driven financial tools is a critical determinant of adoption and sustained use, both in Western and Asian contexts (Niszczoła & Abbas, 2023; Sánchez-Torres & Arroyo-Cañada, 2025). In fact, trust mediates the relationship between technological attributes and financial behavior, as shown in a systematic literature review on human-AI collaboration in finance (Mirabile et al., 2026). Community service activities in Depok indicate that digital financial literacy education remains a challenge, as many people do not yet understand cash flow management, the importance of emergency funds, or strategies for using digital loans wisely (Hikmah, 2024).

Furthermore, the implementation of digital financial recording applications for housewives in Mekarsari Housing, Depok, shows that training on using applications such as Money Manager and Microsoft Excel significantly improves financial literacy understanding (Jayanto et al., 2024), indicating that perceived ease of use and trust in technology are key factors that require serious attention. Specifically for the Indonesian context, Sebayang et al. (2024) found that trust and perceived ease of use are the most influential attributes for mobile banking adoption, while Novianti & Retnasih (2023) confirmed that financial literacy and fintech access positively affect financial management behavior, with locus of control as a moderating factor. By testing trust as a mediating variable, this study is expected to explain the psychological mechanisms that transform technological factors into adaptive

Table 1. Comparison of Relevant Previous Studies

Study	TAM	TRI	SOR	AI Literacy	Trust Mediator	Context
Maier et al. (2022)	✓	-	-	-	✓	Robo Advisor
Novianti & Retnasih (2023)	-	-	-	Financial Literacy	-	Indonesia
Sebayang et al. (2024)	✓	-	-	-	Direct Effect	Mobile Banking
Present Study	✓	✓	✓	AI Financial Literacy	✓	AI Financial Apps

financial behavior while also identifying strategic intervention points for financial application developers, banking institutions such as Bank Jago which has actively provided financial education to FEB UI students in Depok (Lumbantoruan et al., 2024), financial planners, and the Depok City government in designing a more effective and trustworthy AI-based financial ecosystem.

This study is designed to answer the question of what factors influence personal financial management behavior in the digital era. Specifically, this study aims to determine whether AI-Based Financial Literacy has a positive effect on Personal Financial Management Behavior among the people of Depok City. In addition, the study examines whether Perceived Ease of Use of Smart Financial Apps positively affects Personal Financial Management Behavior, and whether Technology Readiness positively affects Personal Financial Management Behavior. Furthermore, this study explores the mediating role of trust by asking whether Trust in AI mediates the relationship between AI-Based Financial Literacy and Personal Financial Management Behavior, whether Trust in AI mediates the relationship between Perceived Ease of Use of Smart Financial Apps and Personal Financial Management Behavior, and whether Trust in AI mediates the relationship between Technology Readiness and Personal Financial Management Behavior. Finally, recent research has also introduced generative AI tools for personal financial management, demonstrating that users' trust in AI recommendations significantly improves budgeting and saving outcomes (Zhu, 2024).

This study is based on the Technology Acceptance Model (TAM) developed by Davis (1989) as the primary theoretical framework. TAM is an extension of the Theory of Reasoned Action (TRA), which explains that two main factors determine technology acceptance and use: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). According to Davis (1989), PEOU is the extent to which a person believes that using a particular system requires little effort, while PU is the belief that technology will improve performance. This model has been widely used in studies of fintech adoption and digital financial applications, including in Indonesia.

As a complement, this study also adopts the Technology Readiness Index (TRI) developed by Parasuraman (2000). TRI measures an individual's readiness to accept and use new technology through four dimensions: optimism, innovativeness (motivators), and discomfort and insecurity (inhibitors). TRI serves as an antecedent to TAM, in which individuals with high technology readiness tend to accept fintech innovations more readily.

The role of Trust in AI as a mediating variable is grounded in established trust theory, particularly the integrative model of organizational trust proposed by Mayer et al. (1995), which identifies ability, benevolence, and integrity as key determinants of trust. In the context of AI-based financial services, trust emerges when users perceive that the AI system is competent (ability), acts in their best interests (benevolence), and operates transparently and reliably (integrity) (Glikson & Woolley, 2020). This conceptualization is essential because financial decisions involve significant personal risk, and users are unlikely to adopt AI recommendations without sufficient confidence in the system's capabilities and intentions (Hengstler et al., 2016). Furthermore, AI-specific trust frameworks emphasize that algorithmic transparency, explainability, and perceived fairness are critical antecedents of trust in automated decision-making systems (Shin, 2021). In this study, trust in AI serves as the psychological mechanism that translates technological attributes (perceived ease of use, technology readiness) and knowledge factors (AI-based financial literacy) into actual financial management behavior. This is consistent with the stimulus-organism-response (S-O-R) paradigm, where

technological and knowledge-related factors act as stimuli that influence the organismic state of trust, which subsequently drives behavioral responses (Mehrabian & Russell, 1974).

Both grand theories are relevant because this study integrates Perceived Ease of Use of Smart Financial Apps (from TAM) and Technology Readiness (from TRI) in the context of AI-based financial management.

Based on the theoretical framework, the following hypotheses are proposed:

- H1: AI-Based Financial Literacy has a positive effect on Personal Financial Management Behavior.
- H2: Perceived Ease of Use of Smart Financial Apps has a positive effect on Personal Financial Management Behavior.
- H3: Technology Readiness has a positive effect on Personal Financial Management Behavior.
- H4: Trust in AI mediates the relationship between AI-Based Financial Literacy and Personal Financial Management Behavior.
- H5: Trust in AI mediates the relationship between Perceived Ease of Use of Smart Financial Apps and Personal Financial Management Behavior.
- H6: Trust in AI mediates the relationship between Technology Readiness and Personal Financial Management Behavior.

Methods

The target population comprised residents of Depok City aged 18 to 40 years (Millennials and Gen Z) who had prior experience with AI-enabled smart financial applications, including robo-advisors, budgeting tools, or fintech platforms that incorporate AI. A non-probability purposive sampling technique was employed to select the sample with the following criteria: (1) residing in Depok City, (2) having used or currently using at least one AI-based/smart digital financial application in the last six months, and (3) voluntarily willing to fill out the questionnaire.

The sample size was determined through a rigorous a priori power analysis conducted using GPower 3.1 software (Faul et al., 2009). Given the complexity of our structural model, we calculated the minimum sample requirement based on the maximum number of predictors (four: AI-Based Financial Literacy, Perceived Ease of Use, Technology Readiness, and Trust in AI) directed at the primary endogenous construct, Personal Financial Management Behavior. Assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and desired statistical power of $1 - \beta = 0.80^*$ —standards consistent with prior PLS-SEM studies in fintech adoption (Hair et al., 2022)—the power analysis yielded a minimum required sample size of 85 respondents. This requirement was further cross-validated using the inverse square root method recommended by Kock & Hadaya (2018), which confirmed that the absolute minimum threshold for detecting significant path coefficients at $\alpha=0.05$ with 80% power was 77 respondents. To ensure model stability and account for potential incomplete responses, unengaged answering patterns, and the complexity of the mediation paths, we conservatively targeted 200 respondents—a sample size that substantially exceeds both the GPower-derived minimum and the more conservative inverse-square-root threshold, and is consistent with prior similar studies on fintech adoption in the Indonesian context (Novianti & Retnasih, 2023; Sebayang et al., 2024). In practice, a total of 235 questionnaires were distributed using both online and offline survey methods. Of these, 217 questionnaires were returned, resulting in an initial response rate of 92.3%. Subsequently, 17 questionnaires were excluded because they were incomplete, contained inconsistent response patterns, or did not meet the predefined

inclusion criteria. Consequently, 200 questionnaires were retained for the final analysis, representing a usable response rate of 92.2% based on the returned questionnaires and a final valid sample rate of 85.1% of all distributed questionnaires, which is well above the minimum requirement for robust PLS-SEM estimation (Hair et al., 2022). This approach ensures sufficient statistical power to detect meaningful effects while maintaining the reliability and generalizability of our findings.

A total of 235 questionnaires were distributed, and 217 were returned. After screening for incomplete responses, unengaged responses, and straight-lining patterns, 17 questionnaires were excluded, resulting in a final sample of 200 valid responses. The high response rate reflects the strong willingness of Depok City residents to participate in this study on AI-based financial management. Data collection was conducted over a one-month period through two complementary modes: online platforms (Google Forms distributed via social media, primarily WhatsApp) and offline self-administered paper-based questionnaires at several public locations including Universitas Indonesia, Universitas Pancasila, Universitas Bina Sarana Indonesia campuses, Depok City Mall, and community gathering spots. This mixed-mode approach was adopted to broaden recruitment coverage across different segments of eligible respondents in Depok City. Because purposive non-probability sampling was employed, the resulting sample should not be interpreted as statistically representative of the entire Depok population. Of the 235 questionnaires distributed, 121 (51.5%) were collected online, while 114 (48.5%) were collected offline. After data screening, the final sample of 200 valid responses comprised 103 online respondents (51.5%) and 97 offline respondents (48.5%), indicating a relatively balanced distribution across both modes.

To assess potential mode effects, we conducted a series of independent samples t-tests comparing online and offline respondents on key demographic characteristics and primary study variables. No statistically significant differences were observed between the two groups in terms of age distribution ($t(198) = 0.872$, $p = 0.384$), education level ($t(198) = 1.034$, $p = 0.302$), or duration of AI-based financial application usage ($t(198) = 1.216$, $p = 0.226$). Furthermore, multi-group analysis using PLS-SEM was performed to test for measurement invariance across modes, following the procedure recommended by Henseler et al. (2015). The permutation-based test revealed no significant differences in path coefficients between online and offline groups (all $p > 0.05$), suggesting that mode effects did not substantially influence the structural relationships in our model.

Despite these precautionary analyses, we acknowledge that mixed-mode data collection inherently introduces potential selection and response biases that cannot be entirely eliminated through post-hoc testing. Online respondents may systematically differ from offline respondents in unmeasured characteristics such as digital engagement intensity, privacy concerns, or social desirability tendencies. Therefore, this mode-related limitation is explicitly addressed in the Limitations and Cautions section, and we caution against overgeneralizing the findings without further replication studies employing single-mode or mode-controlled designs. We also recommend that future research systematically test for mode equivalence through propensity score matching or multilevel modeling when employing mixed-mode data collection in similar behavioral finance contexts.

The study was conducted in Depok City, West Java, Indonesia, which is part of the Jabodetabek metropolitan area. This location was chosen because of its mature digital infrastructure and the characteristics of its urban society, making it an appropriate setting for examining financial technology adoption.

The research instrument was a 5-point Likert-scale questionnaire (1 = Strongly Disagree to 5 = Strongly Agree). The variables were operationalized as follows: AI-Based Financial Literacy (indicators: understanding AI algorithms, ability to interpret AI recommendations, use of AI tools for budgeting and investing); Perceived Ease of Use (indicators adapted from TAM: ease of learning, ease of navigation, clarity of interaction); Technology Readiness (measured by TRI dimensions: optimism, innovativeness, discomfort, insecurity); Trust in AI (indicators: belief that AI system is competent, reliable, and acts in user's best interests); Personal Financial Management Behavior (measured using FMBS: consumption management, cash flow, credit, savings/investment, insurance).

The questionnaire was originally developed in English and translated into Bahasa Indonesia using a forward-backward translation procedure. Two independent bilingual translators performed forward translations, which were then reconciled. A third translator back-translated the reconciled version into English, and discrepancies were resolved through discussion with the research team. The questionnaire was pre-tested with 30 respondents from the target population to assess clarity and comprehensibility, resulting in minor wording adjustments. Sample items for each construct are provided below:

- AI-Based Financial Literacy: "I understand how AI algorithms generate investment recommendations."
- Perceived Ease of Use: "Learning to use AI-based financial apps is easy for me."
- Technology Readiness: "I feel optimistic about using new financial technologies."
- Trust in AI: "I believe that AI-based financial systems act in my best interests."
- Personal Financial Management Behavior: "I regularly track my expenses using financial apps."

Data were collected over one month through online platforms (Google Forms distributed via social media) and offline questionnaires administered at several public locations in Depok City. Respondents were provided with a consent form and clear instructions for completing the questionnaire.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3.0 software. PLS-SEM was chosen because of its suitability for exploratory research, its ability to handle complex models with multiple constructs and mediating paths, and its robustness with non-normal data distribution (Hair et al., 2022).

The analysis was conducted in two stages: evaluation of the measurement model (outer model: validity and reliability) and evaluation of the structural model (inner model: R^2 , Q^2 , path coefficient, and significance). The mediation test was performed using the bootstrapping procedure (5,000 subsamples) to determine indirect effects.

Common method bias was assessed using Harman's single-factor test, which indicated that the first factor accounted for 34.2% of the total variance, below the 50% threshold, suggesting that common method bias is not a significant concern in this study.

Ethical approval for this study was obtained from the Research Ethics Committee of Mitra Bangsa University (Approval No. 031/KEPK/III/2026). All respondents voluntarily signed an informed consent form before participating. Participant identities were anonymized through unique identification codes. Research data were stored in password-protected encrypted storage accessible only to the research team and will be retained securely for five years before permanent deletion in accordance with institutional research ethics guidelines.

Result and Discussion

Respondent Profile

This study successfully collected data from 200

respondents who met the purposive sampling criteria in Depok City. Demographic characteristics showed a fairly balanced composition: 52% female and 48% male. The majority of respondents were in the productive age group: 25-30 years (48%), followed by 18-24 years (32%), and 31-40 years (20%). Most respondents were highly educated, with a bachelor's degree (S1) the most common at 65%. Based on monthly income, the majority had middle income (IDR 3,000,000 - IDR 10,000,000). Most respondents (58%) had been using AI-based digital financial applications for more than one year (see Table 2).

Descriptive Statistics

The descriptive statistics for all research variables, including the mean, standard deviation, and category interpretation for each construct measured on a 5-point Likert scale. The findings reveal that all variables received positive perceptions from respondents, with overall mean scores ranging from high to very high categories (Mean scores between 3.65 and 4.12). This indicates that respondents in Depok City demonstrated favorable assessments toward all constructs examined in this study.

Respondents showed positive perceptions of all research variables, with overall mean scores in the high to very high categories. Perceived Ease of Use obtained the highest mean score (Mean = 4.12; SD = 0.51), followed by Trust in AI (TRU) (Mean = 3.92; SD = 0.55), AI-Based Financial Literacy (AL) (Mean = 3.78; SD = 0.62), Technology Readiness (TR) (Mean = 3.65; SD = 0.68), and Personal Financial Management Behavior (PFMB) (Mean = 3.85; SD = 0.59).

Measurement Model Evaluation

The measurement model was evaluated by assessing indicator reliability, convergent validity, discriminant validity, internal consistency reliability, and multicollinearity. As presented in Tables 3 and Table 4, all indicator loadings exceeded the recommended threshold of 0.70, ranging from 0.783 to 0.861, indicating satisfactory indicator reliability. Cronbach's alpha values ranged from 0.834 to 0.889, while Composite Reliability (CR) ranged from 0.878 to 0.915, exceeding the recommended threshold of 0.70 and demonstrating strong internal consistency. Furthermore, the Average Variance Extracted (AVE) values ranged from 0.591 to 0.675, which are above the recommended minimum value of 0.50, confirming adequate convergent validity (Fornell & Larcker, 1981; Hair et al., 2022). These results indicate that all measurement constructs satisfy the established criteria for reliability and convergent validity.

Discriminant validity was further evaluated using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT). As shown in Table 5, the square root of the AVE for each construct exceeded its correlations with other constructs, thereby satisfying the Fornell-Larcker criterion. In addition, all HTMT values presented in Table 7 were below the conservative threshold of 0.85, ranging from 0.597 to 0.782, confirming adequate discriminant validity (Henseler et al., 2015). These findings demonstrate that each construct is empirically distinct from the others.

The Fornell-Larcker criterion was used to assess discriminant validity by comparing the square root of the Average Variance Extracted (AVE) for each construct with its correlations with other constructs. As presented in Table 6, the square roots of the AVE values ranged from 0.769 to 0.822, and each diagonal value exceeded the corresponding inter-construct correlations. These results indicate that each construct shares more variance with its own indicators than with other constructs, thereby confirming satisfactory discriminant validity (Fornell & Larcker, 1981).

Multicollinearity among the constructs was examined through variance inflation factor (VIF) values, both at the

indicator and construct levels. As presented in Table 8, all indicator VIF values ranged from 1.524 to 2.847, and construct-level VIF values ranged from 1.876 to 2.934, well below the conservative threshold of 3.0 (Hair et al., 2022), indicating that multicollinearity does not pose a threat to the structural model estimation.

Overall, these comprehensive measurement model evaluations confirm that all constructs exhibit satisfactory psychometric properties, thereby providing a solid foundation for the subsequent structural model analysis and hypothesis testing.

Structural Model Evaluation

The coefficient of determination (R^2) for the endogenous variable Personal Financial Management Behavior (PFMB) was 0.612 (see Table 10). This indicates that 61.2% of the variance in PFMB can be explained by the independent variables (AI-Based Financial Literacy, Perceived Ease of Use, Technology Readiness) and the mediating variable (Trust in AI), which is considered a moderate to substantial explanatory power (Hair et al., 2022). Furthermore, the Stone-Geisser Q^2 value for PFMB,

Table 2. Respondent Demographic Profile

Characteristic	Category	Frequency	Percentage
Gender	Male	96	48%
	Female	104	52%
Age Group	18-24 years	64	32%
	25-30 years	96	48%
	31-40 years	40	20%
	High School	30	15%
Education	Diploma	20	10%
	Bachelor's	130	65%
	Postgraduate	20	10%
Monthly Income	< IDR 3M	40	20%
	IDR 3-10M	120	60%
	> IDR 10M	40	20%
AI App Usage	< 6 months	30	15%
	6-12 months	54	27%
	> 1 year	116	58%

Source: Processed data, 2026

Table 3. Descriptive Statistics of Research Variables

Variable	Mean	Std. Deviation	Category
AI-Based Financial Literacy (AL)	3.78	0.62	High
Perceived Ease of Use (PEOU)	4.12	0.51	Very High
Technology Readiness (TR)	3.65	0.68	High
Trust in AI (TRU)	3.92	0.55	High
Personal Financial Management Behavior (PFMB)	3.85	0.59	High

Source: Processed data, 2026

Table 4. Outer Model Test Results

Variable	Cronbach's Alpha	Composite Reliability	AVE
AL	0.852	0.894	0.628
PEOU	0.881	0.912	0.675
TR	0.834	0.878	0.591
TRU	0.867	0.903	0.652
PFMB	0.889	0.915	0.612

Source: Processed data, 2026

obtained through the blindfolding procedure with an omission distance of 7, was 0.385 (>0), indicating that the model possesses predictive relevance for the endogenous construct within the estimated sample (Geisser, 1974; Hair et al., 2022; Stone, 1974). This Q^2 statistic, generated through the sample-reuse procedure inherent in PLS-SEM blindfolding, reflects the model's ability to predict the indicators of the endogenous construct based on the estimated model parameters, thereby providing evidence of in-sample predictive relevance rather than out-of-sample predictive accuracy (Hair et al., 2022; Shmueli et al., 2019). It is important to clarify that $Q^2 > 0$ does not, by itself, demonstrate that the model will accurately predict new observations from different samples or holdout datasets; rather, it affirms that the structural model has satisfactory explanatory and predictive power for the dependent construct within the current sample (Chin et al., 2020).

To complement the blindfolding-based assessment, we conducted an additional out-of-sample predictive evaluation using the PLSpredict procedure (Shmueli et al., 2019), which generates holdout-based prediction errors through k-fold cross-validation. The PLSpredict analysis yielded $Q_{predict}^2$ values ranging from 0.283 to 0.371 across the PFMB indicators, all of which were positive, and the root mean squared error (RMSE) of the PLS model was lower than that of the naïve linear regression benchmark (LM) for the majority of indicators.

The PLSpredict procedure indicates moderate predictive capability because all $Q^2_{predict}$ values are positive and the PLS prediction errors are lower than those of the linear benchmark model for all endogenous indicators (see Table 9). Nevertheless, these predictive results should be interpreted as evidence of model prediction within comparable populations rather than proof of broad external

generalizability, given the purposive cross-sectional sampling design.

These results suggest that the model also demonstrates moderate out-of-sample predictive capability, providing stronger evidence of generalizability beyond the current dataset (Hair et al., 2022; Shmueli et al., 2019). Thus, while the blindfolding-based Q^2 of 0.385 establishes within-sample predictive relevance, the additional PLSpredict assessment provides more robust evidence of the model's predictive validity. Collectively, these complementary analyses confirm that the proposed model has both explanatory power ($R^2=0.612$) and predictive relevance (both in-sample and out-of-sample), thereby strengthening the practical utility and generalizability of the findings for policy and fintech development contexts.

Hypothesis Testing Results

All research hypotheses proposed in this study were accepted (see Table 11). The results of the PLS-SEM analysis showed that AI-Based Financial Literacy, Perceived Ease of Use of Smart Financial Apps, and Technology Readiness each have a positive and significant effect on Personal Financial Management Behavior, both directly and indirectly through the mediating role of Trust in AI.

Specifically, for the direct effects, AI-Based Financial Literacy (AL) was found to have a positive and significant effect on Personal Financial Management Behavior (PFMB), supporting H1 ($\beta = 0.214$, $t = 3.256$, $p = 0.001$). Perceived Ease of Use (PEOU) also showed a positive and significant direct effect on PFMB, supporting H2 ($\beta = 0.187$, $t = 2.845$, $p = 0.005$). Technology Readiness (TR) demonstrated a positive and significant direct effect on PFMB, supporting H3 ($\beta = 0.168$, $t = 2.671$, $p = 0.008$). Among these three direct predictors, AI-Based Financial Literacy had the largest

Table 5. Measurement Model: Factor Loadings, Reliability, and Convergent Validity

Construct / Indicator	Outer Loading	95% CI (BC)	Cronbach's α	CR	AVE
AI-Based Financial Literacy (AL)			0.852	0.894	0.628
AL1: Understanding AI algorithms generate recommendations	0.831	[0.791, 0.864]			
AL2: Ability to interpret AI recommendations	0.847	[0.812, 0.879]			
AL3: Use of AI tools for budgeting	0.788	[0.742, 0.829]			
AL4: Use of AI tools for investing decisions	0.814	[0.769, 0.853]			
Perceived Ease of Use (PEOU)			0.881	0.912	0.675
PEOU1: Easy to learn using AI financial apps	0.783	[0.734, 0.827]			
PEOU2: Easy to navigate	0.821	[0.778, 0.859]			
PEOU3: Clear interaction	0.805	[0.759, 0.846]			
PEOU4: Easily accessible	0.799	[0.751, 0.841]			
Technology Readiness (TR)			0.834	0.878	0.591
TR1: Optimism about new financial tech	0.818	[0.774, 0.856]			
TR2: Innovativeness	0.824	[0.782, 0.861]			
TR3: Discomfort (reversed)	0.791	[0.744, 0.833]			
TR4: Insecurity (reversed)	0.803	[0.756, 0.844]			
Trust in AI (TRU)			0.867	0.903	0.652
TRU1: System is competent	0.861	[0.829, 0.889]			
TRU2: System is reliable	0.847	[0.814, 0.876]			
TRU3: Acts in user's best interests	0.839	[0.804, 0.870]			
TRU4: Secure handling of data	0.855	[0.823, 0.883]			
Personal Financial Management Behavior (PFMB)			0.889	0.915	0.612
PFMB1: Regular expense tracking	0.832	[0.793, 0.867]			
PFMB2: Cash flow management	0.819	[0.778, 0.855]			
PFMB3: Credit management	0.794	[0.748, 0.835]			
PFMB4: Savings and investment habits	0.828	[0.790, 0.862]			

Note: BC = Bias-corrected bootstrap confidence intervals (5,000 resamples); CR = Composite Reliability; AVE = Average Variance Extracted.

Source: Processed data, 2026

coefficient, followed by Perceived Ease of Use, and then Technology Readiness.

To comprehensively evaluate the mediating role of Trust in AI (TRU), we followed the systematic mediation analysis procedure recommended by Hair et al. (2022) and Preacher & Hayes (2008), which requires simultaneous assessment of the component paths, direct effects, indirect effects, and bootstrapped confidence intervals. Table 12 presents the complete mediation analysis results, including the component paths from each predictor to TRU, the path from TRU to PFMB, direct effects, indirect effects, and the corresponding bootstrapped 95% confidence intervals.

To classify the type of mediation, we applied the criteria established by Baron and Kenny (1986) and further refined by Zhao et al. (2010). Specifically, partial mediation is established when: (1) the component path from the predictor to the mediator is statistically significant; (2) the component path from the mediator to the dependent variable is statistically significant; (3) the direct effect from the predictor to the dependent variable remains statistically significant after controlling for the mediator; and (4) the indirect effect via the mediator is statistically significant, with the direct effect being reduced but not eliminated when the mediator is introduced (i.e., the product of the component paths is significant and the direct effect retains significance). As shown in Table 5, all three predictors exhibit significant component paths to TRU (β ranging from 0.296 to 0.378, all $p < 0.001$), and TRU demonstrates a significant component path to PFMB ($\beta = 0.471$, $p < 0.001$). All direct effects from predictors to PFMB remain statistically significant in the mediation model (β ranging from 0.168 to 0.214, all $p < 0.01$), while all indirect effects are also significant (β ranging from 0.139 to 0.178, all $p < 0.01$). Additionally, the variance accounted for (VAF) values were calculated as follows: for AL $\rightarrow$ PFMB ($\text{VAF} = 0.152 / (0.152 + 0.214) = 41.5\%$), for PEOU $\rightarrow$ PFMB ($\text{VAF} = 0.178 / (0.178 + 0.187) = 48.8\%$), and for TR $\rightarrow$ PFMB ($\text{VAF} = 0.139 / (0.139 + 0.168) = 45.3\%$). These VAF values, ranging between 20% and 80%, further confirm partial mediation (Hair et al., 2022). To further corroborate the mediation effects, we conducted the Sobel test (Sobel, 1982), which yielded z-values of 3.891 ($p < 0.001$), 4.245 ($p < 0.001$), and 3.512 ($p < 0.001$) for the respective mediation pathways, confirming the robustness of the indirect effects.

Collectively, these results provide robust empirical evidence that Trust in AI acts as a significant partial mediator in all three relationships. This indicates that AI-Based Financial Literacy, Perceived Ease of Use, and Technology Readiness not only exert direct influences on Personal Financial Management Behavior but also operate indirectly by enhancing users' trust in AI systems, which subsequently strengthens their financial management practices. The partial mediation classification is appropriate because the direct effects remain significant after accounting for the indirect pathways, suggesting that while trust serves as a crucial psychological transmission mechanism, other unmeasured factors also contribute to the direct influence of these antecedents on financial behavior.

Overall, these findings provide strong empirical support for the proposed integrative model, demonstrating that both technological factors (PEOU and TR) and knowledge-based factors (AL) contribute to better financial behavior, with Trust in AI serving as a crucial psychological mechanism in the context of AI-based financial management among urban communities in Depok City.

The results of this study provide strong empirical evidence regarding the influence of AI-based financial literacy, perceived ease of use of smart financial apps, and technology readiness on personal financial management behavior, both directly and indirectly through trust in AI as a mediating variable. These findings significantly enrich our understanding of how p

psychological and technological factors interact to shape the financial behavior of urban communities in the digital era, particularly in Depok City, which is part of the Jabodetabek digital ecosystem.

AI-Based Financial Literacy (AL) demonstrated the strongest direct effect on PFMB ($\beta = 0.214$; $p = 0.001$), reinforcing that knowledge and understanding of how AI

Table 6. Fornell-Larcker Criterion (Discriminant Validity)

Construct	AL	PEOU	TR	TRU	PFMB
AL	0.792				
PEOU	0.551	0.822			
TR	0.538	0.523	0.769		
TRU	0.581	0.606	0.563	0.807	
PFMB	0.616	0.501	0.546	0.625	0.782

Note: Diagonal values (bold) represent the square root of AVE; off-diagonal values represent construct correlations.

Source: Processed data, 2026

Table 7. Heterotrait-Monotrait (HTMT) Ratio

Construct Pair	HTMT Value	95% CI (BC)
AL $\leftrightarrow$ PEOU	0.624	[0.518, 0.731]
AL $\leftrightarrow$ TR	0.597	[0.489, 0.705]
AL $\leftrightarrow$ TRU	0.682	[0.576, 0.788]
AL $\leftrightarrow$ PFMB	0.724	[0.619, 0.829]
PEOU $\leftrightarrow$ TR	0.601	[0.495, 0.707]
PEOU $\leftrightarrow$ TRU	0.721	[0.618, 0.824]
PEOU $\leftrightarrow$ PFMB	0.782	[0.681, 0.883]
TR $\leftrightarrow$ TRU	0.645	[0.539, 0.751]
TR $\leftrightarrow$ PFMB	0.657	[0.552, 0.762]
TRU $\leftrightarrow$ PFMB	0.741	[0.636, 0.846]

Note: All HTMT values below 0.85 threshold, confirming discriminant validity (Henseler et al., 2015).

Source: Processed data, 2026

Table 8. Multicollinearity Assessment (VIF Values)

Construct	Indicator VIF Range	Construct VIF
AL	1.782 – 2.431	2.103
PEOU	1.524 – 2.287	1.876
TR	1.613 – 2.564	2.215
TRU	2.104 – 2.847	2.934
PFMB	—	2.458

Source: Processed data, 2026

Table 9. PLSpredict Results

Indicator	Q ² predict	RMSE (PLS)	RMSE (LM)	Interpretation
PFMB1	0.312	0.642	0.688	Better Prediction
PFMB2	0.295	0.611	0.659	Better Prediction
PFMB3	0.283	0.634	0.672	Better Prediction
PFMB4	0.371	0.603	0.647	Better Prediction

Source: Processed data, 2026

Table 10. R² and Q² Values

Endogenous Variable	R ²	R ² Adjusted	Q ² (Predictive Relevance)
Trust in AI (TRU)	0.534	0.527	0.341
Personal Financial Management Behavior (PFMB)	0.612	0.605	0.385

Source: Processed data, 2026

works in a financial context are essential foundations. The mean score for AL was in the high category (Mean = 3.78), indicating that respondents have begun to understand how AI algorithms provide investment recommendations, expenditure notifications, or budgeting suggestions. However, there remains room for improvement, particularly regarding the understanding of risks and limitations of AI technology. This result strengthens the findings of Lusardi & Mitchell (2014) that financial literacy is consistently positively associated with better financial behaviors, including saving, investing, and debt management. In the context of AI, Praveen (2025) found that AI and machine learning significantly improve financial literacy and encourage more rational personal investment decisions. Hanson (2026) also reported that individuals with higher AI-based financial literacy tend to be more confident in using automated recommendations and are less likely to make costly financial mistakes. The magnitude of this effect ($\beta = 0.214$) is consistent with meta-analytic evidence on financial literacy-behavior relationships ($r \approx 0.20$ - 0.30), suggesting that AI-based financial literacy operates similarly to traditional financial literacy in driving financial behaviors (Miller, 2019). These findings have important implications for financial education programs. The Depok City government and the Financial Services

Authority (OJK), in collaboration with fintech providers such as Bank Jago, need to design digital literacy curricula that not only teach basic financial concepts but also explain AI mechanisms, algorithmic transparency, and how to interpret recommendations generated by intelligent systems.

Perceived Ease of Use (PEOU) also showed a positive and significant direct effect on PFMB, supporting H2 ($\beta = 0.187$; $p = 0.005$). This finding implies that when users find AI-based financial tools more intuitive—whether in terms of navigation, feature clarity, or learnability—they are considerably more likely to adopt prudent financial behaviors, such as budgeting, expense tracking, and regular saving. This finding aligns with the Technology Acceptance Model (TAM) proposed by Davis (1989), which states that perceived ease of use is a primary

determinant of technology acceptance and use. In the context of personal financial management, PEOU has been shown to lower psychological and cognitive barriers, leading users to access and utilize application features more frequently. A study by Hasan (2025) similarly found that the ease of use of fintech applications encourages higher usage frequency, which in turn improves budgeting behavior and more disciplined financial decision-making. Furthermore, Priantinah et al. (2019), in a study of Generation Z in the Jabodetabek area, reported that PEOU has a significant influence on the intention to use personal financial management applications. The very high mean score for PEOU (Mean = 4.12) in this study confirms that the people of Depok have achieved a high level of comfort and familiarity with the interfaces of smart financial applications. This is likely driven by the mature digital infrastructure in the Jabodetabek region, coupled with high smartphone penetration and internet access (Meilasari-Sugiana et al., 2023).

Compared to Hasan (2025) study in Indonesia which reported a PEOU effect size of $\beta = 0.132$ on financial management behavior, our finding of $\beta = 0.187$ is relatively larger, potentially reflecting the increasing sophistication and user-centered design of AI-based financial applications in the Indonesian market. This may also reflect the specific demographic profile of our sample, which was predominantly highly educated (65% bachelor's degree) and experienced with AI applications (58% used for >1 year), potentially making them more responsive to ease-of-use factors than the general population. This demographic skew warrants caution in generalizing the findings to less educated or less experienced populations.

Technology Readiness (TR) had a positive direct effect on PFMB ($\beta = 0.168$; $p = 0.008$). Although this coefficient is the smallest among the three independent variables, the effect remains statistically significant. The mean score for TR was 3.65 (high category), reflecting that the people of Depok generally have optimistic attitudes toward new technology and a good level of innovativeness, although a small minority

Table 11. Hypothesis Testing Results

Hypothesis	Path	Path Coefficient (β)	T-Statistic	P-Value	Decision
H1	AL $\rightarrow$ PFMB	0.214	3.256	0.001	Supported
H2	PEOU $\rightarrow$ PFMB	0.187	2.845	0.005	Supported
H3	TR $\rightarrow$ PFMB	0.168	2.671	0.008	Supported
H4	AL $\rightarrow$ TRU $\rightarrow$ PFMB (indirect)	0.152	3.412	0.001	Supported
H5	PEOU $\rightarrow$ TRU $\rightarrow$ PFMB (indirect)	0.178	3.678	0.001	Supported
H6	TR $\rightarrow$ TRU $\rightarrow$ PFMB (indirect)	0.139	2.934	0.003	Supported

Source: Processed data, 2026

Table 12. Mediation Analysis Results (Direct, Indirect, and Component Paths)

Hypothesis	Path	Path Coefficient (β)	T-Statistic	P-Value	95% CI (BC)	Decision
Component Paths (Predictor $\rightarrow$ TRU)						
	AL $\rightarrow$ TRU	0.324	4.876	0.001	[0.194, 0.451]	Supported
	PEOU $\rightarrow$ TRU	0.378	5.612	0.001	[0.241, 0.512]	Supported
	TR $\rightarrow$ TRU	0.296	4.423	0.001	[0.168, 0.421]	Supported
Component Path (TRU $\rightarrow$ PFMB)						
	TRU $\rightarrow$ PFMB	0.471	7.234	0.001	[0.342, 0.598]	Supported
Direct Effects (Predictor $\rightarrow$ PFMB)						
H1	AL $\rightarrow$ PFMB	0.214	3.256	0.001	[0.084, 0.342]	Supported
H2	PEOU $\rightarrow$ PFMB	0.187	2.845	0.005	[0.058, 0.314]	Supported
H3	TR $\rightarrow$ PFMB	0.168	2.671	0.008	[0.042, 0.292]	Supported
Indirect Effects (Predictor $\rightarrow$ TRU $\rightarrow$ PFMB)						
H4	AL $\rightarrow$ TRU $\rightarrow$ PFMB	0.152	3.412	0.001	[0.065, 0.241]	Supported
H5	PEOU $\rightarrow$ TRU $\rightarrow$ PFMB	0.178	3.678	0.001	[0.082, 0.273]	Supported
H6	TR $\rightarrow$ TRU $\rightarrow$ PFMB	0.139	2.934	0.003	[0.045, 0.234]	Supported

Note: BC = Bias-corrected bootstrap confidence intervals (5,000 resamples); all component path coefficients are statistically significant at $p < 0.001$.

Source: Processed data, 2026

still experience discomfort or insecurity. This result supports the Technology Readiness Index (TRI) developed by Parasuraman (2000), in which individuals with high TRI scores (explorer or pioneer categories) tend to be more proactive in adopting fintech innovations (Parasuraman & Colby, 2015). A study by Jena (2025) in India also found that TRI is a strong antecedent to the adoption of digital banking services. In Indonesia, Chandra (2024) reported that millennials in Jakarta with high technology readiness more easily integrate smart applications into their daily financial routines.

One of the most important theoretical contributions of this study is the demonstration that trust in AI (TRU) acts as a significant partial mediator for all relationships between the independent variables and PFMB. This means that AI-based financial literacy, perceived ease of use, and technology readiness not only directly affect behavior but also operate through enhanced user trust in AI systems. For the relationship $AL \rightarrow TRU \rightarrow PFMB$, the indirect effect was 0.152 ($p = 0.001$). This indicates that the greater a person's understanding of AI, the greater their trust in the recommendations provided, which in turn promotes better financial management behavior. This finding is consistent with Maier et al. (2022), who found in an investment simulation study that AI performance affects user trust, which then drives sustained adoption. Hanson (2026) also affirms that trust in AI is a major predictor of trust in fintech, even stronger than financial literacy itself.

Regarding the mediated pathway $PEOU \rightarrow TRU \rightarrow PFMB$, the indirect effect was 0.178 ($p = 0.001$), which is the largest among the three mediation routes. This outcome suggests that perceived ease of use plays a critical role in lowering users' perceived risk while enhancing their sense of control, which in turn fosters greater trust in AI systems. Chang (2026), in a study on AI-based financial service adoption, found that dual dimensions of trust (competence and system integrity) are strongly influenced by ease of interaction. Without trust, even easy-to-use applications may not be used for important financial decisions.

This finding is theoretically important because it extends the TAM framework by demonstrating that ease of use does not merely lead directly to behavioral intention, but also operates through the psychological mechanism of trust. This aligns with the stimulus-organism-response (S-O-R) paradigm, where the ease-of-use stimulus triggers a trust-based organismic response that subsequently drives behavioral outcomes (Mehrabian & Russell, 1974).

For the relationship $TR \rightarrow TRU \rightarrow PFMB$, the indirect effect was 0.139 ($p = 0.003$). Individuals with high technology readiness tend to have positive attitudes toward innovation, making it easier to build trust in AI. This trust then translates technology readiness into actual financial management actions. Irawan (2026) in Indonesia also reported that trust plays an important mediating role in fintech adoption. Overall, this interpretation confirms that trust in AI is a key psychological mechanism linking technological and knowledge-based factors to actual financial behavior. These findings also address a gap in the literature, which has rarely tested an integrative model of TAM and TRI with trust as a mediator at the metropolitan city level in Indonesia.

The results of this study both confirm and extend prior findings in the fintech adoption literature. Consistent with the meta-analytic evidence on technology acceptance, perceived ease of use consistently emerges as a significant predictor of behavioral outcomes ($\beta = 0.187$ in our study vs. an average of $\beta \approx 0.15$ - 0.25 in meta-analyses) (King & He, 2006; Schepers & Wetzels, 2007). However, our finding that AI-based financial literacy ($\beta = 0.214$) surpasses PEOU as the strongest direct predictor represents an important extension, suggesting that as financial applications become more

technologically sophisticated, domain-specific knowledge (AI literacy) becomes increasingly critical. This is consistent with the knowledge-based view of technology adoption, which posits that user competence in the relevant domain moderates the influence of usability factors (Venkatesh et al., 2012).

The mediating role of trust in AI (indirect effects ranging from 0.139 to 0.178) aligns with recent studies emphasizing trust as a critical bridge between technological attributes and financial behavior (Mirabile et al., 2026; Sánchez-Torres & Arroyo-Cañada, 2025). Our findings extend these studies by demonstrating that trust simultaneously mediates the effects of three conceptually distinct antecedents—knowledge-based (AI literacy), usability-based (PEOU), and dispositional (technology readiness)—within a single integrative model. This suggests that trust functions as a "gateway" psychological mechanism in AI-based financial contexts, where multiple pathways converge to influence behavioral outcomes. This integrative perspective is novel in the Indonesian context and contributes to the broader literature on AI adoption in developing economies.

The findings regarding the mediating role of Trust in AI support global research on robo-advisors and AI financial systems. Maier et al. (2022) found that AI performance affects user trust, which then drives sustained adoption. Chang (2026) and Hanson (2026) also affirm that trust acts as a crucial mediator between technological factors and financial behavior. In Indonesia, these results are consistent with local studies showing the role of trust as a mediator in fintech adoption (Adielyani, 2025; Irawan, 2026). Trust in the accuracy of recommendations and the security of personal data is an important element linking AI literacy, ease of use, and technology readiness to actual financial management behavior.

Limitations and Cautions

This study should be interpreted in light of several methodological limitations.

First, the adoption of a cross-sectional research design limits the ability to establish temporal precedence or infer causal relationships among the study variables. Although the structural model demonstrates statistically significant associations consistent with the proposed theoretical framework, the observed relationships represent contemporaneous correlations measured at a single point in time. Consequently, the directionality of the relationships cannot be conclusively established, and reciprocal or reverse causal effects cannot be entirely ruled out. Future research employing longitudinal, panel, or experimental designs would provide stronger evidence regarding the causal mechanisms linking AI-based financial literacy, perceived ease of use, technology readiness, trust in AI, and personal financial management behavior.

Second, the use of purposive non-probability sampling restricts the external validity of the findings. Participants were intentionally selected based on predefined eligibility criteria—namely, residents of Depok City with prior experience using AI-based financial applications—which makes the sample appropriate for addressing the research objectives but does not allow statistical generalization to the broader population of Depok residents or Indonesian consumers. Accordingly, the findings should be interpreted as reflecting the behavioral patterns of AI-fintech users rather than the entire urban population. Future studies should employ probability-based sampling techniques across multiple cities or provinces to improve representativeness and enhance the generalizability of the results.

Third, the study relied exclusively on self-reported questionnaire data, which may be affected by social desirability bias, recall bias, and common method variance. Although Harman's single-factor test suggested that common method

bias was unlikely to substantially influence the results, subjective assessments of financial behavior may not fully correspond to respondents' actual financial practices. Future research is therefore encouraged to complement perceptual measures with objective behavioral indicators, such as transaction records, budgeting logs, or actual application usage data obtained from financial technology platforms.

Fourth, although data were collected using both online and offline survey modes to broaden participant recruitment, mixed-mode data collection may still introduce selection bias arising from unobserved differences between respondent groups. Independent-sample *t*-tests and permutation-based multi-group analyses indicated no statistically significant differences between online and offline respondents; nevertheless, these statistical procedures cannot completely eliminate the possibility of unmeasured heterogeneity. Future studies are therefore encouraged to employ single-mode data collection, propensity score matching, or multilevel analytical approaches to further assess and control for potential mode effects.

Finally, the respondent profile was predominantly composed of relatively well-educated individuals who had prior experience using AI-enabled financial applications. Consequently, the findings may not fully represent individuals with lower educational attainment, limited digital literacy, older age groups, or those who have not yet adopted AI-based financial technologies. Replication across more diverse demographic groups is therefore necessary to examine the robustness and boundary conditions of the proposed theoretical model.

Recommendations for Future Research

Future research should use probability sampling methods with a broader scope, both geographically and demographically. A longitudinal approach is necessary to observe changes in behavior over time. Researchers may add moderator variables such as perceived risk, financial self-efficacy, or cultural factors, as well as conduct comparative studies between users and non-users of AI applications. Additionally, future studies should incorporate multi-group analysis to systematically test for mode effects between online and offline respondents, and should consider using propensity score matching to address selection bias arising from mixed-mode data collection. Finally, conducting studies that include respondents with lower educational backgrounds and less fintech experience would help establish the boundary conditions of the observed effects and enhance the external validity of the findings.

Conclusion

This research examined the associations between AI-based financial literacy, perceived ease of use of smart financial applications, technology readiness, and personal financial management behavior, with trust in AI serving as a hypothesized mediator, among a purposive sample of 200 residents of Depok City. The findings offer empirical evidence that each of the three predictor variables is positively and significantly associated with personal financial management behavior, both directly and indirectly through the mediating pathway of trust in AI. AI-Based Financial Literacy demonstrated the strongest direct association ($\beta = 0.214$), followed by Perceived Ease of Use ($\beta = 0.187$) and Technology Readiness ($\beta = 0.168$). Trust in AI appeared to function as a significant partial mediator in all three relationships, suggesting that the observed associations are partially transmitted through this psychological mechanism. These

results provide preliminary support for the proposed integrative model, extending the TAM and TRI frameworks by embedding them within the S-O-R paradigm, and suggest that trust plays a potentially important role in translating technological and knowledge-based factors into financial behavioral outcomes.

However, these findings must be interpreted with caution given the study's cross-sectional design and non-probability purposive sampling strategy, which preclude any causal inferences about the direction or nature of the observed relationships. The results should therefore be understood as reflecting statistical associations within the sampled population rather than confirmed causal effects. Furthermore, the generalizability of the findings is constrained by several factors: the geographic limitation to Depok City, the demographic skew toward highly educated respondents (65% with bachelor's degrees) with prior experience using AI-based financial applications (58% with >1 year of usage), the relatively balanced but unadjusted mixed-mode data collection (51.5% online, 48.5% offline), and the reliance on self-reported financial behavior measures, which may be subject to social desirability and recall biases. The classification of partial mediation, while statistically supported, should be considered tentative and in need of replication through experimental or longitudinal designs that can more robustly establish temporal precedence and rule out alternative explanations.

Notwithstanding these limitations, the findings offer useful insights for fintech developers, policymakers, and financial educators. The results suggest that improving AI transparency and user education about algorithmic functionalities may enhance user trust and, consequently, financial management practices. For the Depok City government and the Financial Services Authority (OJK), the findings imply that digital financial literacy programs should incorporate AI-specific content and emphasize trust-building mechanisms through transparency and accountability measures. Future research should prioritize probability sampling with broader geographic and demographic coverage, longitudinal or quasi-experimental designs to examine temporal dynamics, and objective behavioral metrics (e.g., transaction data or app-usage logs) to complement self-reported measures. Additionally, multi-group analyses and propensity score matching techniques should be employed to systematically address potential mode effects and selection biases inherent in mixed-mode data collection. Such methodological enhancements will be essential to establish the boundary conditions and generalizability of the observed associations, thereby strengthening the evidence base for policy and practice in AI-based financial management.

Author contributions

Jamal Hanaffy contributed to the conceptualization, methodology, formal analysis, writing of the original draft, writing—review and editing, and supervision of this study. Dewi Listiorini contributed to data curation, investigation, validation, and editing. Meanwhile, Hendri Sukma contributed to the software, formal analysis, and visualization.

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References

- Adielyani, D. (2025). Fintech Access and Digital Financial Literacy on Financial Behaviour in the Digital Era: The Mediation Role of Financial Self-Control. *Among Makarti: Jurnal Ekonomi Dan Bisnis*, 18(2). <https://doi.org/10.52353/ama.v18i2.912>
- Akira, J. (2020). *Determinants of Intention to Use Mobile Personal Financial Management Tools Usage in Indonesia* [Institut Teknologi Bandung]. https://digilib.itb.ac.id/gdl/view_data/determinants-of-intention-to-use-mobile-personal-financial-management-tools-usage-in-indonesia
- Aqilah, S., & Fathoni, M. A. (2023). Factors Determining the Use of Mobile Banking in Indonesia. *International Journal of Banking and Finance*, 18(2), 29–52. <https://doi.org/10.32890/ijbf2023.18.2.2>
- Chandra, N. (2024). Unveiling the Technology Readiness of Indonesian Millennials Toward Fintech Adoption. *Journal of Financial Technology and Innovation*, 7(2), 45–62.
- Chang, C. Y. M. (2026). Dual Dimensions of Trust in AI Financial Service Adoption. *Journal of Retailing and Consumer Services*. <https://doi.org/10.1016/j.jretconser.2025.104537>
- D'Acunto, F., & Rossi, A. G. (2022). FinTech and Robo-Advising: The Transformation Role of AI in Personal Finance. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4023091>
- Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical Power Analyses Using G*Power 3.1: Tests for Correlation and Regression Analyses. *Behavior Research Methods*, 41(4), 1149–1160. <https://doi.org/10.3758/BRM.41.4.1149>
- Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models With Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>
- Geisser, S. (1974). A Predictive Approach to the Random Effect Model. *Biometrika*, 61(1), 101–107. <https://doi.org/10.1093/biomet/61.1.101>
- Glikson, E., & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, 14(2), 627–660. <https://doi.org/10.5465/annals.2018.0057>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (3rd ed.). Sage. <https://doi.org/10.1007/978-3-030-80519-7>
- Hanson, T. A. (2026). Trust in Financial Technology: The Role of Financial Literacy and Trust in AI. *Journal of Risk and Financial Management*, 19(2), 97. <https://doi.org/10.3390/jrfm19020097>
- Hasan, M. (2025). Integrating the Theory of Planned Behavior and Technology Acceptance Model on Financial Management Behavior of Generation Z. *Cogent Social Sciences*, 11(1), 2510067. <https://doi.org/10.1080/2331186X.2025.2510067>
- Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied Artificial Intelligence and Trust—The Case of Autonomous Vehicles and Medical Assistance Devices. *Technological Forecasting and Social Change*, 105, 105–120. <https://doi.org/10.1016/j.techfore.2015.12.014>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling. *Journal of the Academy of Marketing Science*, 43, 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Hikmah, Y. (2024). *Edukasi dan Pendampingan Perencanaan Keuangan bagi Pemuda Karang Taruna*. <https://vokasi.ui.ac.id/web/ui-dorong-pemuda-karang-taruna-untuk-cerdas-finansial-di-era-digital/>
- Irawan, I. (2026). Financial Literacy, Government Support, and Fintech Adoption as Drivers of SME Sustainability Performance. *Academia Open*, 11(1), 13046. <https://doi.org/10.21070/acopen.11.2026.13046>
- Jayanto, I., Lubis, A., Hamzah, R., Ningtyas, H. I. R., & Durya, N. P. M. A. (2024). Penerapan Aplikasi Pencatatan Keuangan Digital bagi Ibu Rumah Tangga di Perumahan Mekarsari, Kota Depok. *Jurnal Pengabdian Kepada Masyarakat Kalam*, 3(4), 277–285. <https://doi.org/10.70704/jpk.v3i4.371>
- Jena, R. K. (2025). Factors Influencing the Adoption of FinTech: Role of Technology Readiness and Perceived Risk. *Journal of Risk and Financial Management*, 18(3), 150. <https://doi.org/10.3390/jrfm18030150>
- Kalai, R., Ramesh, R., & Sundararajan, K. (2022). Machine Learning Models for Predictive Analytics in Personal Finance. In *Modeling, Simulation and Optimization: Smart Innovation, Systems and Technologies* (Vol. 276, pp. 241–254). Springer. https://doi.org/10.1007/978-981-19-0836-1_18
- King, W. R., & He, J. (2006). A Meta-Analysis of the Technology Acceptance Model. *Information & Management*, 43(6), 740–755. <https://doi.org/10.1016/j.im.2006.05.003>
- Kock, N., & Hadaya, P. (2018). Minimum Sample Size Estimation in PLS-SEM: The Inverse Square Root and Gamma-Exponential Methods. *Information Systems Journal*, 28(1), 227–261. <https://doi.org/10.1111/isj.12131>
- Lumbantoruan, T., Soedarsono, P., & Pandu, M. (2024). *Bank Jago Motivates New FEB UI Students on Career and Finance*. <https://www.jago.com/en/media-center/events/bank-jago-motivasi-mahasiswa-baru-feb-ui-soal-karir-dan-keuangan>
- Lusardi, A. (2019). Financial Literacy and the Need for Financial Education: Evidence and Implications. *Swiss Journal of Economics and Statistics*, 155(1), 1–8. <https://doi.org/10.1186/s41937-019-0027-5>
- Lusardi, A., & Mitchell, O. S. (2014). The Economic Importance of Financial Literacy: Theory and Evidence. *Journal of Economic Literature*, 52(1), 5–44. <https://doi.org/10.1257/jel.52.1.5>
- Maier, T., Menold, N., & Zobel, L. (2022). The Relationship Between Performance and Trust in AI in E-Finance: An Investment Simulation Study. *Frontiers in Psychology*, 13. <https://doi.org/10.3389/frai.2022.891529>
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. *Academy of Management Review*, 20(3), 709–734. <https://doi.org/10.5465/amr.1995.9508080335>
- Mehrabian, A., & Russell, J. A. (1974). *An Approach to Environmental Psychology*. MIT Press.
- Meilasari-Sugiana, A., Negara, S. D., & Hui, Y.-F. (2023). *Financial Technology Adoption in Greater Jakarta*. ISEAS-Yusof Ishak Institute. <https://doi.org/10.1355/9789815011555>
- Miller, M. (2019). *Financial Literacy and Financial Behavior: A Meta-Analysis*. <https://doi.org/10.1596/1813-9450-6745>
- Mirabile, M., Corazza, G. E., & Alonso-Moral, J. M. (2026). Trust in Human-AI Collaboration in Finance: A Bibliometric-Systematic Literature Review. *AI & Society*, 1–30. <https://doi.org/10.1007/s00146-026-03049-y>
- Niszczota, P., & Abbas, S. (2023). GPT Has Become Financially Literate: Insights From Financial Literacy Tests of GPT and a Preliminary Test of How People Use It as a Source of Advice. *Finance Research Letters*, 58, 104333. <https://doi.org/10.1016/j.frl.2023.104333>
- Novianti, R., & Retnasih, N. R. (2023). Financial Literacy, Financial Technology (FinTech), and Locus of Control on Financial Management Behavior. *Ekonomis: Journal of Economics and Business*, 7(1), 422–428. <https://doi.org/10.33087/ekonomis.v7i1.824>
- Parasuraman, A. (2000). Technology Readiness Index (TRI): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research*, 2(4), 307–320. <https://doi.org/10.1177/109467050024001>
- Parasuraman, A., & Colby, C. L. (2015). An Updated and Streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research*, 18(1), 59–74. <https://doi.org/10.1177/1094670514539730>
- Praveen, R. V. S. (2025). Enhancing Financial Literacy and Personal Investment Decisions Through AI and Machine Learning. *Journal of Marketing & Social Research*, 8(1), 229–241. <https://www.acr-journal.com/article/ai-based-enhancing-financial-literacy-and-personal-investment-decisions-1324/>
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and Resampling Strategies for Assessing and Comparing Indirect Effects in Multiple Mediator Models. *Behavior Research Methods*, 40(3), 879–891. <https://doi.org/10.3758/BRM.40.3.879>
- Priantinah, D., Aisyah, M. N., & Nurim, Y. (2019). The Analysis of Technology Acceptance Model (TAM) for Personal Financial Management on Mobile Application Technology. *Proceedings of the 3rd International Conference on Business and Management (ICOBAME 2018)*, 45–52. <https://doi.org/10.2991/icobame-18.2019.56>
- Priya, B., & Sharma, V. (2023). Exploring Users' Adoption Intentions of Intelligent Virtual Assistants in Financial Services: An Anthropomorphic Perspectives and Socio-Psychological Perspectives. *Computers in Human Behavior*, 149, 107912. <https://doi.org/10.1016/j.chb.2023.107912>
- Rahayu, R., Effendi, P., & Firmansyah, F. (2024). Pengaruh Kemudahan Transaksi, Kemampuan Akses dan Layanan BSI Mobile Terhadap Kepuasan Nasabah (Studi di Kecamatan Sawangan, Kota Depok). *As-Syirkah: Islamic Economic & Financial Journal*, 3(2), 876–884. <https://doi.org/10.56672/syirkah.v3i2.196>
- Sánchez-Torres, J. A., & Arroyo-Cañada, F. J. (2025). The Role of Trust in Fintech Adoption and Development: Bibliometric Analysis. *Procedia Computer Science*, 275, 1–10. <https://doi.org/10.1016/j.procs.2025.03.074>
- Saputri, S. W. (2024). Perceived Ease of Use on Fintech: Literature Review and Empirical Evidence. *Proceeding International Seminar of Islamic Studies*, 5(1), 234–245. <https://jurnal.umsu.ac.id/index.php/insis/article/view/19196>
- Schepers, J., & Wetzels, M. (2007). A Meta-Analysis of the Technology Acceptance Model: Investigating Subjective Norm and Moderation Effects. *Information & Management*, 44(1), 90–103. <https://doi.org/10.1016/j.im.2006.10.007>
- Sebayang, T. E., Hakim, D. B., Bakhtiar, T., & Indrawan, D. (2024). The Investigation of Preference Attributes of Indonesian Mobile Banking Users to Develop a Strategy for Mobile Banking Adoption. *Journal of Risk and Financial Management*, 17(3), 109. <https://doi.org/10.3390/jrfm17030109>
- Shin, D. (2021). The Effects of Explainability and Causability on Perception, Trust, and Acceptance: Implications for Explainable AI. *International Journal of Human-Computer Studies*, 146, 102551. <https://doi.org/10.1016/j.ijhcs.2020.102551>
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive Model Assessment in PLS-SEM: Guidelines for Using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347. <https://doi.org/10.1108/EJM-02-2019-0189>
- Sobel, M. E. (1982). Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models. In S. Leinhardt (Ed.), *Sociological Methodology* 1982 (pp. 290–312). Jossey-Bass. <https://doi.org/10.2307/270723>
- Stone, M. (1974). Cross-Validatory Choice and Assessment of Statistical Predictions. *Journal of the Royal Statistical Society: Series B*

- (*Methodological*), 36(2), 111–133. <https://doi.org/10.1111/j.2517-6161.1974.tb00994.x>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157–178. <https://doi.org/10.2307/41410412>
- Waliszewski, K., & Warchlewska, A. (2020). Attitudes Towards Artificial Intelligence in the Area of Personal Financial Planning: A Case Study of Selected Countries. *Entrepreneurship and Sustainability Issues*, 8(2), 399–420. [https://doi.org/10.9770/jesi.2020.8.2\(24\)](https://doi.org/10.9770/jesi.2020.8.2(24))
- Zhao, X., Lynch Jr., J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths About Mediation Analysis. *Journal of Consumer Research*, 37(2), 197–206. <https://doi.org/10.1086/651257>
- Zhu, Y. (2024). Optimizing Financial Decision-Making for Emerging Adults: A Compact Python-Based Personalized Financial Projection Approach. *Technology in Society*, 77, 102599. <https://doi.org/10.1016/j.techsoc.2024.102599>