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Abstract: The rapid adoption of AI-based investment recommendation systems has reshaped financial decision-making among Generation Z investors in emerging digital markets. The behavioural mechanism linking AI effectiveness to investment performance remains unclear. This study examines the effects of AI recommendation accuracy, investment goal orientation, technology readiness, and perceived risk on investment performance, with trust in AI recommendation as a mediating variable. Using a quantitative explanatory design and PLS-SEM analysis on 301 Generation Z investors, the findings show that AI recommendation accuracy is the strongest determinant of trust. Trust significantly enhances investment performance and mediates the relationship between perceived accuracy and performance. Investment goal orientation and technology readiness directly improve performance but are not fully mediated by trust, while perceived risk affects trust but not performance. These results extend the technology acceptance model by highlighting trust as a key behavioural mechanism linking AI system effectiveness to financial outcomes in emerging markets.

Keywords: trust in AI; investment performance; AI recommendation systems; Generation Z; Fintech adoption; Indonesia.

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1 Introduction

The rapid expansion of digital investment platforms in Indonesia has reshaped the national capital market, particularly through the growing participation of younger investors. By 2025, more than 54.96% of individual investors are projected to be under the age of 30, collectively managing assets exceeding IDR 50.75 trillion (Sudaryanto et al., 2023). Unlike developed markets, where institutional investors continue to dominate trading activity, Indonesia has experienced a marked surge in retail participation driven by digitally native young individuals. This demographic shift has accelerated the adoption of artificial intelligence (AI)-based investment recommendation systems across asset classes, including equities, cryptocurrencies and foreign exchange (Alliata and Bozagi, 2025). AI-based systems increasingly function as digital financial advisory mechanisms (Bashir et al., 2023). Although AI-driven systems offer substantial potential to enhance investment performance through large-scale data processing and timely insights, their effectiveness depends fundamentally on investors' trust in the accuracy and reliability of algorithmic recommendations (Bashir et al., 2024; Zarifis and Cheng, 2024).

Despite the increasing integration of AI into financial decision-making, trust in algorithmic recommendations remains fragile and context-dependent (Schmidt et al., 2020). Concerns regarding transparency, alignment with individual objectives and perceived financial risk continue to constrain reliance on AI-based advisory tools. These challenges are particularly salient in emerging digital markets such as Indonesia, where rapid technological adoption coexists with uneven financial literacy, evolving regulation and limited institutional oversight (Saleem et al., 2023). Understanding how trust develops and how it enhances investment outcomes is therefore of critical importance. Existing research highlights AI recommendation accuracy as a key driver of decision quality in stock trading, cryptocurrency markets and algorithmic portfolio management (Vidler, 2024). Trust has similarly been identified as a mechanism linking technological performance with user acceptance and behavioural outcomes (Trinh et al., 2025). Trust formation is shaped not only by perceived accuracy but also by transparency and compatibility with user goals (Orbán and Stefkovics, 2025), as well as reduced perceptions of risk (Klingbeil et al., 2024). However, empirical evidence on the trust-performance relationship remains concentrated in developed economies, leaving emerging markets underexplored.

This gap is particularly relevant given that, although Generation Z investors dominate market participation in Indonesia, the total assets under their management remain relatively modest (Susada, 2025). This suggests that widespread adoption of AI tools does not necessarily translate into improved financial outcomes, potentially due to insufficient trust. Prior studies have largely examined the direct effects of technological characteristics on investment decisions (Kaplan and Haenlein, 2020), while the mediating

role of trust has received limited attention, particularly in emerging markets (Chua et al., 2023). To address this gap, the present study conceptualises trust in AI recommendations as a central mechanism linking AI recommendation accuracy with investment performance among young Indonesian investors. Drawing on the technology acceptance model (TAM) (Davis, 1987), trust is reconceptualised as a performance-enhancing mechanism within the digital investment value chain. The model further integrates investment goal orientation, technology readiness and perception of risk as determinants of trust formation, offering a comprehensive framework for understanding AI-enabled investment behaviour in emerging digital markets.

Accordingly, this study addresses the following research questions:

- RQ1: How does trust in AI recommendations mediate the relationship between AI recommendation accuracy and investment performance among young investors in Indonesia?
- RQ2: To what extent do investment goal orientation, technology readiness and perception of risk influence trust in AI recommendations and subsequently shape investment performance?

The novelty of this research lies in empirically positioning trust as a behavioural mechanism linking AI recommendation accuracy to investment performance within an emerging market context. While previous studies have acknowledged the importance of algorithmic accuracy in shaping investment decisions (Jafri et al., 2024), limited attention has been devoted to examining how trust translates technological effectiveness into measurable financial outcomes, particularly among young investors in developing economies. By integrating trust into an extended TAM framework and situating the analysis within Indonesia's rapidly evolving digital investment landscape, this study contributes to the growing literature on AI-driven financial decision-making and offers actionable implications for the development of trustworthy AI-based investment platforms.

2 Theoretical framework

The TAM, proposed by Davis (1987), provides a foundational framework for explaining technology adoption. It posits that perceived usefulness (PU) and perceived ease of use (PEOU) shape users' attitudes, which subsequently influence behavioural intention and actual system use. PU refers to the extent to which a technology enhances task performance, whereas PEOU concerns the perceived effort required to use it (Venkatesh et al., 2003). Over time, TAM has been extended to incorporate additional psychological and contextual variables to better account for technology adoption in complex digital settings.

In AI-based investment platforms, TAM offers a useful framework for understanding how investors evaluate algorithmic recommendation systems. However, the original model does not explicitly incorporate trust or risk, two critical elements in financial contexts characterised by uncertainty and high stakes. Research in digital finance suggests that acceptance of AI-driven systems depends not only on PU and ease of use but also on the degree of trust placed in algorithmic outputs (Glikson and Woolley, 2020). In investment environments, trust functions not merely as an adoption facilitator

but as a prerequisite for sustained utilisation and effective decision-making. Incorporating trust into TAM therefore enables a more comprehensive explanation of how technological effectiveness translates into investment outcomes. Accordingly, this study conceptualises trust in AI recommendation as a central mechanism linking AI recommendation accuracy with investment performance. The model further integrates investment goal orientation, technology readiness and perception of risk as antecedents of trust formation, offering an extended TAM framework to examine AI-enabled financial decision-making among young investors.

Within AI-driven financial services, recommendation accuracy constitutes a fundamental determinant of system effectiveness and user confidence (Shin, 2020). Accuracy extends beyond technical precision and serves as a perceptual indicator of system reliability, consistency and informational quality (Nazaretsky et al., 2025). When AI-generated recommendations align consistently with market realities and investor expectations, they foster cognitive trust by reducing uncertainty and reinforcing perceptions of system competence (Vidler, 2024). From a TAM perspective, accurate outputs enhance PU by demonstrating the system's capacity to improve decision quality (Sabir et al., 2023). Pasupuleti (2025) further contends that precise and transparent recommendations facilitate trust calibration, enabling users to form realistic mental models of algorithmic capabilities and limitations. Repeated exposure to reliable recommendations strengthens perceptions of dependability, creating a reinforcing cycle in which trust promotes greater reliance on AI systems and deeper integration into decision-making processes (Ayyildiz and Iskenderoglu, 2024).

Moreover, a direct relationship between accuracy and performance is theoretically plausible. Superior algorithmic accuracy may enhance investment outcomes by optimising trade timing, improving asset selection and reducing exposure to unprofitable positions, irrespective of the user's trust level. Despite growing recognition of accuracy as a critical technological factor, prior studies have predominantly examined its direct effects on adoption and performance. The mediating role of trust, particularly within emerging digital markets, remains underexplored (Orbán and Stefkovics, 2025). Accordingly, this study posits that AI recommendation accuracy enhances investment performance both directly and indirectly through the formation of trust in AI recommendation.

H1 AI recommendation accuracy positively affects trust in AI recommendation.

H2 AI recommendation accuracy positively affects investment performance.

H3 Trust in AI recommendation mediates the relationship between AI recommendation accuracy and investment performance.

Investment decision-making is increasingly influenced by digital technologies that process complex financial data and deliver personalised recommendations (Maier et al., 2022). AI-based systems allow investors to integrate real-time market insights with individual financial objectives, supporting strategic portfolio management and mitigating cognitive biases (Pillai, 2023; Saleem et al., 2023). Within this context, investment goal orientation reflects the clarity and strategic consistency with which individuals define and pursue financial objectives across time horizons.

From a TAM perspective, investors with clearly defined goals are more likely to perceive AI systems as useful when recommendations align with their priorities (Wang et al., 2023). Eren (2024) finds that goal-oriented investors demonstrate stronger

intentions to adopt robo-advisory services, particularly when outputs support long-term planning. Alignment between AI recommendations and investor objectives further strengthens trust in AI recommendation and enhances financial outcomes (Singh and Karamcheti, 2025). Thus, investment goal orientation provides a behavioural foundation through which trust develops and contributes to improved investment performance.

H4 Investment goal orientation positively affects trust in AI recommendation.

H5 Investment goal orientation positively affects investment performance.

H6 Trust in AI recommendation mediates the relationship between investment goal orientation and investment performance.

Technology readiness reflects individuals' psychological predisposition toward adopting and utilising new technologies, encompassing drivers such as optimism and innovativeness, as well as inhibitors including discomfort and insecurity (Mahmood et al., 2023). In AI-driven investment environments, technology readiness plays a critical role in shaping how investors perceive algorithmic systems and develop confidence in their functionality. Investors with higher technology readiness are more likely to actively engage with AI-based tools, effectively interpret digital market signals, and leverage automated recommendations to enhance portfolio performance (Fatima and Chakraborty, 2024). From a TAM-based perspective, technological familiarity strengthens PU and ease of use, which subsequently facilitates trust formation in AI systems (Mitchell, 2025). Uren and Edwards (2023) further suggest that technologically prepared users are more inclined to view AI recommendations as reliable and beneficial, thereby reinforcing Trust in AI recommendation.

Beyond trust formation, technology readiness also directly influences investment performance by enabling investors to exploit advanced digital functionalities more efficiently. Through enhanced analytical capabilities and faster decision execution, technologically prepared investors gain strategic advantages in volatile financial markets.

H7 Technology readiness positively affects trust in AI recommendation.

H8 Technology readiness positively affects investment performance.

H9 Trust in AI recommendation mediates the relationship between technology readiness and investment performance.

Financial decision-making inherently involves uncertainty, making perception of risk a central factor influencing investor behaviour and trust in technological systems (Ikhsan et al., 2025). In AI-based investment contexts, perceived risk encompasses not only potential financial losses but also concerns regarding algorithmic reliability, prediction errors, and ethical implications (Appiah and Agblewornu, 2025). High levels of perceived risk tend to undermine confidence in AI recommendations, leading users to question system credibility and reduce reliance on algorithmic advice (Cao et al., 2025). While explainable AI mechanisms can enhance transparency and system understanding, their effectiveness is contingent upon users' baseline risk perceptions (Balasubramaniam et al., 2023).

Leichtmann et al. (2023) argue that when perceived risk is elevated, transparency alone may be insufficient to fully restore trust, as concerns regarding financial consequences continue to dominate decision-making processes. Empirical evidence further indicates that heightened risk perception often triggers defensive investment

behaviours, including decision delays, avoidance of automated recommendations, and overly conservative portfolio strategies, which can negatively affect investment performance (Ahmad and Shah, 2022). This negative effect may be amplified among young investors in emerging markets like Indonesia, where financial safety nets are limited and experiences with technological failures or fraud may heighten sensitivity to algorithmic risks.

Accordingly, perception of risk is conceptualised as a barrier factor that weakens trust in AI recommendation and diminishes the effectiveness of AI-driven investment decision-making.

H10 Perception of risk negatively affects trust in AI recommendation.

H11 Perception of risk negatively affects investment performance.

H12 Trust in AI recommendation mediates the relationship between perception of risk and investment performance.

Trust in AI recommendation represents investors' confidence in the competence, reliability, and integrity of algorithmic decision-support systems (Sellamuthu et al., 2023). As AI increasingly mediates financial decision-making, trust functions as a critical psychological mechanism determining whether users rely on algorithmic outputs or revert to manual judgement. High levels of trust enable investors to act more decisively on AI-generated recommendations, particularly in volatile market conditions (Back et al., 2023). Consistent with TAM extensions, PU and system reliability reinforce trust formation, fostering greater adoption and sustained reliance on AI systems (Maier et al., 2022). When trust is appropriately calibrated, AI recommendations facilitate informed decision-making, improved portfolio optimisation, and enhanced financial performance (Onyenahazi and Antwi, 2024). However, excessive or miscalibrated trust may expose investors to algorithmic biases or systemic risks, highlighting the importance of balanced trust development (Klingbeil et al., 2024). Financial advice may moderate the relationship between AI usage and investment outcomes (Bashir et al., 2024).

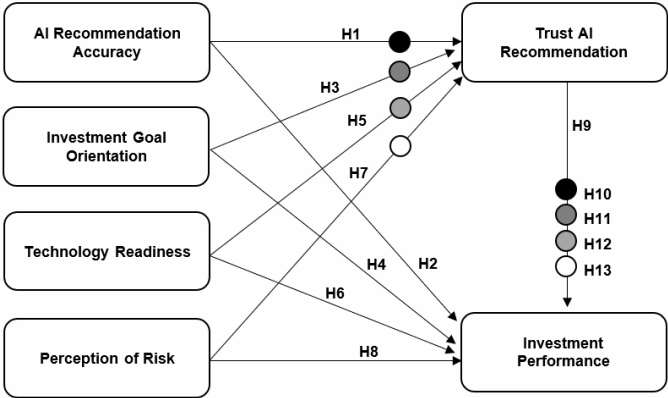
Within the proposed framework, trust in AI recommendation operates not only as an outcome of key technological and behavioural antecedents, such as AI recommendation accuracy, investment goal orientation, and technology readiness, but also as a central driver of investment performance. As investors develop confidence in the reliability, competence, and consistency of AI-generated recommendations, they are more likely to rely on algorithmic insights in their decision-making processes, particularly in complex and volatile financial markets. This reliance facilitates more informed, timely, and strategic investment actions, enabling AI system effectiveness to be translated into tangible financial outcomes. Accordingly, trust functions as a critical behavioural mechanism through which AI-based recommendation systems exert their influence on investment success, leading to the hypothesis:

H13 Trust in AI recommendation positively affects investment performance.

Based on the theoretical foundations and empirical evidence discussed above, this study develops a conceptual framework illustrating the relationships among AI recommendation accuracy, investment goal orientation, technology readiness, perception of risk, trust in AI recommendation, and investment performance. The framework positions trust as a central behavioural mechanism linking technological characteristics

and psychological predispositions to investment outcomes. The proposed research model is presented in Figure 1.

Figure 1 Conceptual framework diagram



3 Research design

This study adopts a quantitative explanatory design to examine the direct and indirect effects of AI recommendation accuracy, investment goal orientation, technology readiness, and perception of risk on investment performance, with trust in AI recommendation serving as a mediating variable among Generation Z investors. Generation Z was selected because they are the most digitally connected generation and are among the fastest-growing users of AI-enabled investment platforms and fintech services in Indonesia. Their high level of technology adoption makes them an appropriate group for investigating AI-assisted investment behaviour. Data were collected through an online survey distributed via Google Forms using validated measurement scales and a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 3 (Magno et al., 2024), appropriate for mediation and predictive analysis. The study was conducted in Indonesia from January to May 2025 across major urban centres, namely Jakarta, Bandung, Surabaya, Yogyakarta, and Semarang. These cities were selected because they represent Indonesia’s major economic and digital hubs, with high levels of digital technology adoption, strong fintech development, and a large number of active Generation Z retail investors, making them suitable locations for examining AI-based investment behaviour.

Although this study was conducted in the Indonesian context, its findings will provide valuable insights for other developing countries and emerging markets that share similar characteristics, including rapid fintech growth, increasing adoption of AI in financial services, and growing participation of young retail investors. However, the findings should be generalised to developed countries with caution, as differences in digital maturity, investor behaviour, and regulatory frameworks may influence the applicability of the results.

The population comprised Indonesian Generation Z investors (born 1997–2012) aged 18–28 who had used AI-based investment platforms, (e.g., robo-advisors and fintech applications) for at least six months and generated investment income within the past month. Using purposive sampling, 301 valid responses were obtained. The demographic characteristics of respondents are summarised in Table 1.

Table 1 Respondent profile

<i>Variable</i>		<i>Frequency</i>	<i>Percentage (%)</i>
Gender	Male	180	59.80
	Female	120	39.87
Type of investment	Stocks	121	40.20
	Crypto	90	29.90
	Forex	90	29.90
Investment duration	> 1 year	30	9.97
	1–5 years	120	39.87
	5–10 years	90	29.90
	< 10 years	61	20.27
Age	18–23	120	39.87
	24–28	181	60.13
Investment expenditure	< IDR 1,000,000	90	29.90
	IDR 1,000,000–IDR 5,000,000	110	36.54
	IDR 5,000,000–IDR 10,000,000	70	23.26
	> IDR 10,000,000	31	10.30

Operationalisation refers to translating conceptual variables into measurable indicators (Shouxin, 2024). AI recommendation accuracy, investment goal orientation, technology readiness, perception of risk, trust in AI recommendation, and investment performance were measured using multi-item constructs adapted from established literature. Each construct consisted of between three and five indicators to ensure adequate construct reliability and validity.

Table 2 Operational variable

<i>Variable</i>	<i>Definition</i>	<i>Indicators</i>	<i>Source</i>
AI recommendation accuracy	The extent to which investors perceive that AI-based recommendation systems provide precise, reliable, and relevant investment suggestions aligned with their financial objectives.	• Perceived accuracy of AI recommendations • Relevance of recommendations to investment goals • Consistency of AI-generated suggestions	Bahoo et al. (2024) and Kim et al. (2021)
Investment goal orientation	The degree to which individuals have clear, structured, and consistent investment objectives guiding their financial decision-making.	• Clarity of investment objectives • Focus on long-term financial goals • Consistency in pursuing investment targets	Busch et al. (2021) and Khan et al. (2021)

Table 2 Operational variable (continued)

<i>Variable</i>	<i>Definition</i>	<i>Indicators</i>	<i>Source</i>
Technology readiness	The psychological pre-disposition of individuals to embrace and utilise new digital technologies in investment activities.	• Optimism toward technology benefits • Innovativeness in adopting new financial technologies • Discomfort with complex technologies (reverse-coded) • Insecurity regarding technology reliability (reverse-coded)	Sudaryanto et al. (2023)
Perception of risk	Investors' subjective assessment of uncertainty and potential negative outcomes associated with AI-based investment decisions.	• Perceived likelihood of financial loss • Uncertainty regarding AI prediction reliability • Concern about unexpected market out-comes • Fear of algorithmic errors	Nair et al. (2025)
Trust in AI recommendation	The level of confidence investors place in the reliability, competence, and integrity of AI-based recommendation systems.	• Perceived transparency of AI recommendations • Reliability of AI-generated advice • Ethical handling of investment information • Consistency of system performance	Hassan et al. (2025)
Investment performance	Investors' perceived improvement in financial outcomes and decision effectiveness resulting from the use of AI-based recommendations.	• Improvement in investment returns • Growth of investment portfolio value • Stability of investment outcomes • Effectiveness of investment decisions	BaniHani et al. (2024) and Roppelt et al. (2024)

4 Results

This section presents the empirical findings derived from PLS-SEM. The analysis was conducted in two stages: evaluation of the measurement model and assessment of the structural model. The measurement model was examined in terms of convergent validity, discriminant validity and internal consistency reliability to ensure robust construct measurement. The structural model was then assessed by analysing the coefficient of determination (R^2) and testing the significance of hypothesised paths using bootstrapping. Collectively, these procedures evaluate the model's explanatory power and predictive

robustness. The outer model evaluation aims to assess the adequacy of the measurement instruments in capturing the latent constructs included in the study. In line with PLS-SEM procedures, three key criteria were examined: convergent validity, discriminant validity, and reliability. Convergent validity assesses the degree to which multiple indicators of a construct are in agreement. Discriminant validity ensures that each construct is empirically distinct from other constructs in the model. Reliability evaluates the internal consistency of the indicators in measuring each construct. The results indicate that the measurement model demonstrates satisfactory psychometric properties and is suitable for subsequent structural analysis.

Table 3 Convergent validity

<i>Indicator</i>	<i>ARA</i>	<i>IGO</i>	<i>IP</i>	<i>PR</i>	<i>TIAI</i>	<i>TR</i>
ARA1	0.924	–	–	–	–	–
ARA2	0.932	–	–	–	–	–
ARA3	0.951	–	–	–	–	–
IGO1	–	0.862	–	–	–	–
IGO2	–	0.858	–	–	–	–
IGO3	–	0.843	–	–	–	–
IP1	–	–	0.742	–	–	–
IP2	–	–	0.781	–	–	–
IP3	–	–	0.851	–	–	–
IP4	–	–	0.834	–	–	–
PR1	–	–	–	0.843	–	–
PR2	–	–	–	0.863	–	–
PR3	–	–	–	0.877	–	–
PR4	–	–	–	0.774	–	–
TIAI1	–	–	–	–	0.860	–
TIAI2	–	–	–	–	0.859	–
TIAI3	–	–	–	–	0.844	–
TIAI4	–	–	–	–	0.855	–
TR1	–	–	–	–	–	0.866
TR2	–	–	–	–	–	0.827
TR3	–	–	–	–	–	0.848
TR4	–	–	–	–	–	0.873

Notes: ARA: AI recommendation accuracy

IGO: Investment goal orientation

IP: Investment performance

PR: Perception of risk

TIAI: Trust in AI recommendation

TR: Technology readiness.

Source: SmartPLS 3 output

Convergent validity was assessed by examining the outer loading values of each indicator on its respective construct. According to established guidelines, indicator loadings above 0.70 indicate adequate convergent validity, reflecting a strong association between

indicators and their latent variables (Hair et al., 2019; Sarstedt et al., 2022). The results show that all indicators exhibit loading values exceeding the recommended threshold of 0.70, ranging from 0.742 to 0.951. The highest loading was observed for ARA3 (0.951), indicating a strong representation of the AI recommendation accuracy construct. The lowest loading was recorded for IP1 (0.742); however, this value remains acceptable and suggests sufficient contribution to the investment performance construct. Overall, the findings confirm that all indicators demonstrate strong convergent validity and effectively measure their respective latent constructs. The detailed outer loading values are presented in Table 3.

Discriminant validity evaluates whether each construct is empirically distinct from other constructs in the model, ensuring that each latent variable captures a unique phenomenon (Hair et al., 2019). In this study, discriminant validity was assessed using the Fornell-Larcker criterion, which requires the square root of the average variance extracted (AVE) for each construct to exceed its correlations with other constructs (Fornell and Larcker, 1981).

As shown in Table 4, the square root of AVE (diagonal values) for all constructs is greater than the corresponding inter-construct correlations. This indicates that each construct shares more variance with its own indicators than with other constructs in the model. For example, the square root of AVE for AI recommendation accuracy (0.936) exceeds its correlations with investment goal orientation (0.819), investment performance (0.812), perception of risk (0.839), technology readiness (0.808) and trust in AI recommendation (0.868). Similarly, trust in AI recommendation demonstrates a square root of AVE (0.892) that is higher than its correlations with other constructs. Overall, these findings confirm satisfactory discriminant validity, supporting the distinctiveness of the latent variables and the robustness of the measurement model.

Table 4 Discriminant validity

<i>Variable</i>	<i>ARA</i>	<i>IGO</i>	<i>IP</i>	<i>PR</i>	<i>TR</i>	<i>TIAI</i>
ARA	0.936	–	–	–	–	–
IGO	0.819	0.856	–	–	–	–
IP	0.812	0.820	0.891	–	–	–
PR	0.839	0.835	0.803	0.840	–	–
TR	0.808	0.846	0.832	0.818	0.854	–
TIAI	0.868	0.823	0.824	0.829	0.811	0.892

Source: SmartPLS 3 output

Reliability assessment examines the internal consistency of indicators in representing their respective latent constructs. In PLS-SEM, reliability is commonly evaluated using Cronbach's alpha and composite reliability (CR), with values above 0.70 indicating satisfactory internal consistency (Hair et al., 2019; Sarstedt et al., 2022). AVE is also reported to assess convergent validity, with values exceeding 0.50 suggesting that constructs explain more than half of the variance in their indicators.

As shown in Table 5, all constructs exhibit strong reliability, with Cronbach's alpha ranging from 0.817 to 0.929 and CR from 0.891 to 0.955, exceeding recommended thresholds. All AVE values are above 0.50 (0.626–0.875), confirming adequate convergent validity. These results demonstrate satisfactory internal consistency and support the robustness of the measurement model for subsequent structural analysis.

Table 5 Reliability

<i>Variable</i>	<i>Cronbach's alpha</i>	<i>Composite reliability</i>	<i>AVE</i>
AI recommendation accuracy	0.929	0.955	0.875
Investment goal orientation	0.817	0.891	0.732
Investment performance	0.850	0.893	0.626
Perception of risk	0.860	0.906	0.706
Technology readiness	0.876	0.915	0.729
Trust in AI recommendation	0.877	0.915	0.730

Source: SmartPLS 3 output

The structural (inner) model evaluation aims to examine the hypothesised relationships among latent constructs and to assess the model's explanatory power. Unlike the measurement model, which focuses on indicator reliability and validity, the inner model emphasises the strength, direction, and significance of the causal paths among variables. In accordance with PLS-SEM procedures, the structural model was evaluated using the coefficient of determination (R^2) and hypothesis testing through bootstrapping techniques. The R^2 values indicate the proportion of variance in endogenous constructs explained by the exogenous variables, providing an assessment of the model's predictive capability. Hypothesis testing further examines whether the proposed relationships are statistically supported.

The coefficient of determination (R^2) was used to evaluate the explanatory power of the structural model. R^2 values represent the extent to which the independent variables collectively explain variance in the dependent constructs. According to established guidelines, R^2 values of 0.25, 0.50, and 0.75 may be interpreted as weak, moderate, and substantial explanatory power, respectively (Hair et al., 2019). As shown in Table 6, the model demonstrates substantial explanatory power for both endogenous constructs. Investment Performance exhibits an R^2 value of 0.778, indicating that approximately 77.8% of the variance in investment outcomes is explained by AI recommendation accuracy, investment goal orientation, technology readiness, perception of risk, and trust in AI recommendation. Meanwhile, trust in AI recommendation demonstrates an R^2 value of 0.827, suggesting that 82.7% of its variance is explained by the associated antecedent variables. The high R^2 values indicate that the proposed model possesses strong explanatory and predictive capability, suggesting that the technological, behavioural, and psychological factors incorporated in this study collectively explain the primary determinants of both trust in AI recommendations and investment performance. This substantial explanatory power is likely attributable to the comprehensive integration of key factors underlying AI-assisted investment decision-making. AI recommendation accuracy represents the quality and reliability of recommendations generated by AI systems, technology readiness reflects investors' readiness to adopt AI technologies, investment goal orientation captures the strategic motivations underlying investment decisions, perception of risk explains how investors evaluate potential uncertainty, while trust in AI recommendation serves as the central psychological mechanism linking these factors to investment outcomes. Collectively, these constructs provide a holistic explanation of investor behaviour, enabling the model to account for a large proportion of the variance in both endogenous variables. Nevertheless, although the high R^2 values demonstrate the model's strong ability to explain the phenomenon under investigation,

they should not be interpreted as evidence that all determinants influencing the two endogenous constructs have been fully captured.

These values exceed the threshold for substantial explanatory power, indicating that the proposed model possesses strong predictive capability in explaining both trust formation and investment performance among young investors. The high R^2 values further suggest that the integration of technological and behavioural factors within the extended TAM framework provides a comprehensive explanation of AI-driven investment decision-making in the Indonesian context.

Table 6 R-square test results

<i>Variable</i>	<i>R²</i>	<i>Adjusted R²</i>
Investment performance	0.778	0.775
Trust in AI recommendation	0.827	0.825

Source: SmartPLS 3 output

Hypothesis testing was conducted using PLS-SEM. The significance of the proposed relationships was assessed through bootstrapping with 5,000 resamples, generating t-statistics and p-values for each structural path. A two-tailed significance level of 5% was applied, with t-values ≥ 1.96 indicating statistical significance (Hair et al., 2019; Sarstedt et al., 2022). The results are summarised in Table 7.

Table 7 Hypothesis testing results

<i>Hypothesis</i>	<i>Path</i>	<i>β</i>	<i>t-value</i>	<i>p-value</i>	<i>Result</i>
H1	ARA $\rightarrow$ TIAI	0.537	11.743	0.000	Accepted
H2	ARA $\rightarrow$ IP	0.122	1.967	0.050	Accepted
H3	ARA $\rightarrow$ TIAI $\rightarrow$ IP	0.121	3.141	0.002	Accepted
H4	IGO $\rightarrow$ TIAI	0.155	2.661	0.008	Accepted
H5	IGO $\rightarrow$ IP	0.187	2.581	0.010	Accepted
H6	IGO $\rightarrow$ TIAI $\rightarrow$ IP	0.035	1.917	0.056	Rejected
H7	TR $\rightarrow$ TIAI	0.127	2.353	0.019	Accepted
H8	TR $\rightarrow$ IP	0.302	4.818	0.000	Accepted
H9	TR $\rightarrow$ TIAI $\rightarrow$ IP	0.029	1.955	0.051	Rejected
H10	PR $\rightarrow$ IP	0.111	1.729	0.084	Rejected
H11	PR $\rightarrow$ TIAI	0.145	2.691	0.007	Accepted
H12	PR $\rightarrow$ TIAI $\rightarrow$ IP	0.033	1.808	0.071	Rejected
H13	TIAI $\rightarrow$ IP	0.225	3.182	0.002	Accepted

Source: SmartPLS 3 output

Overall, the findings provide strong empirical support for the central role of trust in AI recommendation in linking technological and behavioural antecedents to investment performance. AI recommendation accuracy has a strong positive effect on trust in AI recommendation ($\beta = 0.537$, $p < 0.001$), supporting H1, and a marginally significant direct effect on investment performance ($\beta = 0.122$, $p = 0.050$), supporting H2. Its indirect effect on investment performance via trust is also significant ($\beta = 0.121$, $p = 0.002$), confirming the mediating role of trust (H3). These results indicate that the

performance impact of accurate AI recommendations is strengthened when investors develop trust in the system.

Investment goal orientation positively influences trust in AI recommendation ($\beta = 0.155$, $p = 0.008$; H4) and investment performance ($\beta = 0.187$, $p = 0.010$; H5). However, its indirect effect via Trust is not significant at the 5% level ($\beta = 0.035$, $p = 0.056$), leading to the rejection of H6. This suggests that goal orientation affects performance primarily through direct behavioural alignment rather than mediated trust. This finding may indicate that Generation Z investors who possess clear investment goals tend to rely on their predetermined financial objectives and investment strategies rather than developing additional trust in AI recommendations. In other words, goal-oriented investors may use AI as a supporting analytical tool rather than as the primary basis for investment decisions, thereby weakening the mediating role of trust. This also suggests that having well-defined investment objectives is, by itself, sufficient to enhance investment performance, regardless of the degree of trust placed in AI systems.

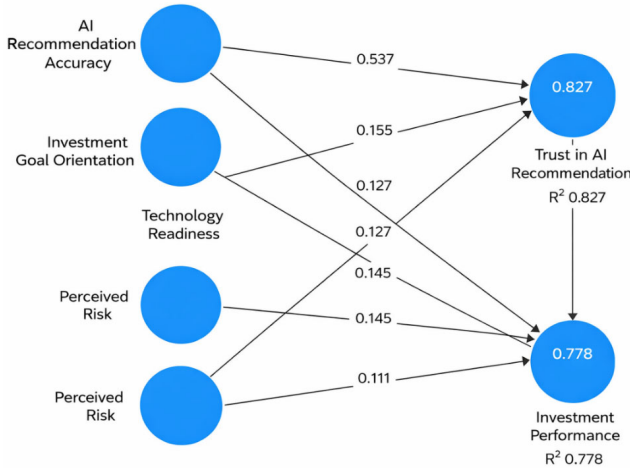
Technology readiness significantly affects trust in AI recommendation ($\beta = 0.127$, $p = 0.019$; H7) and has a strong direct effect on investment performance ($\beta = 0.302$, $p < 0.001$; H8). Nevertheless, the indirect effect through trust is not statistically significant ($\beta = 0.029$, $p = 0.051$), resulting in the rejection of H9. Thus, technologically prepared investors appear to achieve improved outcomes largely through direct mechanisms. A plausible explanation is that investors with high technology readiness already possess the knowledge, digital skills, and confidence required to effectively utilise AI-based investment platforms. Consequently, their superior investment performance is more likely driven by their ability to interpret, evaluate, and apply AI-generated information independently, rather than by an increased psychological reliance on AI recommendations. Therefore, technology readiness contributes directly to better investment decisions without requiring trust to function as an intermediary mechanism.

Perception of risk positively influences trust in AI recommendation ($\beta = 0.145$, $p = 0.007$; H11) but does not directly affect investment performance ($\beta = 0.111$, $p = 0.084$; H10 rejected). Its indirect effect via trust is also non-significant ($\beta = 0.033$, $p = 0.071$; H12 rejected). Finally, trust in AI recommendation significantly enhances investment performance ($\beta = 0.225$, $p = 0.002$; H13), confirming its role as a key behavioural mechanism. Overall, 9 of the 13 hypotheses were supported. The non-significant indirect effect suggests that although higher perceived risk encourages investors to place greater trust in AI recommendations, this increased trust alone is insufficient to generate superior investment performance. Investment outcomes remain dependent on the quality of investment execution, market dynamics, and investors' ability to integrate AI recommendations with their own financial judgement. Therefore, risk perception appears to influence the psychological acceptance of AI rather than serving as an effective pathway for improving investment returns through trust.

Figure 2 presents the structural model illustrating the hypothesised relationships among the latent constructs and their corresponding standardised path coefficients. The model demonstrates the central role of trust in AI recommendation as a key mediating mechanism linking technological and behavioural antecedents to investment performance. AI recommendation accuracy exhibits the strongest influence on trust in AI recommendation ($\beta = 0.537$), indicating that perceived system accuracy is the primary driver of trust formation among young investors. Investment goal orientation ($\beta = 0.155$)

and technology readiness ($\beta = 0.127$) also contribute positively to trust, suggesting that both goal clarity and technological preparedness enhance confidence in AI-based recommendations. In contrast, perceived risk shows a weaker but significant relationship with trust ($\beta = 0.145$), highlighting the sensitivity of trust formation to perceived uncertainty in digital investment environments.

Figure 2 Structural model diagram (see online version for colours)



Investment performance is directly influenced by trust in AI recommendation ($\beta = 0.225$), confirming trust as a critical behavioural mechanism through which AI system effectiveness translates into improved financial outcomes. Beyond this mediated pathway, technology readiness ($\beta = 0.302$), investment goal orientation ($\beta = 0.187$) and AI recommendation accuracy ($\beta = 0.122$) also exert direct effects on investment performance. These findings indicate that technological competence and goal alignment contribute substantially to investment outcomes, independently of trust. By contrast, perceived risk demonstrates a weak and non-significant direct effect ($\beta = 0.111$), suggesting that its influence operates primarily through psychological rather than performance-based channels. The model exhibits strong explanatory power, with R^2 values of 0.827 for trust in AI recommendation and 0.778 for investment performance. This indicates that the proposed framework effectively captures the principal drivers of trust formation and investment outcomes within AI-driven investment contexts.

Overall, the hypothesis testing provides robust empirical support for the proposed trust-based mechanism within the AI-enabled investment decision framework. Of the thirteen hypothesised relationships, nine are statistically supported, while four are not significant, reflecting a structurally sound and realistic model. AI recommendation accuracy emerges as the most influential antecedent of trust in AI recommendation, while trust itself is confirmed as a key determinant of investment performance. Furthermore, investment goal orientation and technology readiness demonstrate meaningful direct effects on performance, highlighting the importance of behavioural alignment and technological preparedness. In contrast, perceived risk primarily shapes trust formation rather than directly influencing outcomes. The unsupported hypotheses (H6, H9, and H12) also provide important theoretical insights by suggesting that trust does not

universally mediate the relationship between all antecedent variables and investment performance. Instead, certain behavioural characteristics, such as strong investment goals and high technological readiness, appear to influence investment outcomes through direct cognitive and behavioural mechanisms. Similarly, although perceived risk increases investors' reliance on AI recommendations, this psychological response alone does not necessarily translate into better investment performance, indicating that successful investment outcomes depend on the interaction between investor capability, AI support, and external market conditions. Collectively, these findings validate the extended TAM framework and underscore the pivotal role of trust in enhancing AI-driven investment performance among young investors in emerging digital markets.

5 Discussion

The findings indicate that AI recommendation accuracy is a strong predictor of trust in AI recommendation among Generation Z investors. When AI systems are perceived as accurate, reliable and aligned with investors' financial objectives, trust increases significantly. Perceived accuracy functions as a cognitive signal of competence, reducing uncertainty and strengthening confidence in algorithmic outputs. This is consistent with prior research identifying perceived accuracy as a central driver of trust in AI-enabled services (Chua et al., 2023). This finding is also consistent with the TAM, which argues that users develop stronger trust and acceptance when a technology is perceived as useful and capable of improving decision quality. Accurate AI recommendations therefore enhance PU and reinforce investors' confidence in AI-supported investment decisions. AI recommendation accuracy also has a moderate but significant direct effect on investment performance, indicating that accurate AI insights contribute to improved outcomes. However, the relatively modest magnitude suggests that accuracy alone is insufficient to optimise performance, particularly in emerging markets where behavioural biases, such as herding and speculative decision-making, remain prevalent (Jain and Vanzara, 2023; Saleem et al., 2023). Importantly, mediation analysis reveals that trust in AI recommendation significantly strengthens the effect of AI recommendation accuracy on investment performance. Trust therefore operates as a key behavioural mechanism translating technological effectiveness into financial outcomes. In line with (Maier et al., 2022), repeated exposure to accurate recommendations reinforces reliability perceptions and sustained reliance on AI systems.

Investment goal orientation has a positive effect on trust in AI recommendation, indicating that investors with clearly defined financial objectives are more likely to regard AI recommendations as credible and useful. Clear goal structures enable Generation Z investors to assess the relevance and alignment of recommendations with their personal strategies, thereby reinforcing trust in AI-based systems (Busch et al., 2021). Goal clarity thus functions as a cognitive framework through which trust in algorithmic advice is formed. This result is further supported by goal setting theory, which suggests that individuals with specific and clearly defined goals process information more systematically and are more likely to evaluate decision-support technologies based on their ability to facilitate goal achievement. Investment goal orientation also demonstrates a direct positive effect on investment performance. Investors with structured objectives tend to exhibit greater discipline, reduced impulsivity and more strategic resource allocation, leading to improved outcomes. This finding

supports prior research emphasising goal-driven behaviour as a key determinant of financial success (Yang et al., 2020). However, the mediating role of trust in AI recommendation between investment goal orientation and investment performance is not supported. This suggests that goal-oriented investors enhance performance primarily through direct behavioural alignment rather than through trust-based reliance on AI systems, contrasting with findings reported by Bashir et al. (2025). A possible explanation is that investors with well-defined investment goals possess sufficient self-regulation and decision confidence to translate their objectives directly into investment actions. Consequently, trust in AI becomes less essential because their investment behaviour is primarily driven by internal cognitive planning rather than dependence on external technological assistance.

Technology readiness positively influences trust in AI recommendation, suggesting that psychological preparedness to adopt digital technologies enhances confidence in AI-based investment systems. Generation Z investors, characterised by high digital literacy and technological openness, are more likely to perceive AI systems as reliable and beneficial, thereby strengthening trust formation. This finding is consistent with Arce-Urriza et al. (2025), who identify familiarity and technological optimism as key enablers of trust. From the perspective of technology readiness theory, individuals with higher technological optimism and innovativeness generally exhibit lower psychological resistance toward emerging technologies, allowing trust to develop more rapidly. Technology readiness also exerts a strong direct effect on investment performance, indicating that technologically prepared investors are better able to utilise digital platforms, interpret AI-generated insights and execute decisions effectively. However, the indirect effect through trust in AI recommendation is not significant, suggesting that performance improvements arise primarily from direct technological competence rather than trust-based mechanisms. This unexpected finding may indicate that technologically capable investors rely more on their digital competencies than on psychological trust when making investment decisions. Their ability to interpret AI-generated information independently reduces the mediating role of trust in achieving superior investment performance.

The findings reveal that perceived risk positively influences trust in AI recommendation, contrary to the initial assumption of a negative effect. This suggests that heightened awareness of investment uncertainty motivates Generation Z investors to rely more on AI-based recommendations as a means of reducing informational ambiguity and enhancing decision confidence. Rather than undermining trust, risk perception appears to encourage greater dependence on technologically supported decision-making in emerging digital markets. This finding can be interpreted through the lens of behavioural finance, which argues that investors experiencing higher uncertainty actively seek additional information and decision-support mechanisms to reduce ambiguity. In this context, AI recommendations function as a cognitive aid rather than a source of additional uncertainty. In contrast, perceived risk does not exhibit a significant direct effect on investment performance (H10), indicating that risk awareness alone does not determine financial outcomes. Similarly, the indirect effect of perceived risk on investment performance through trust in AI recommendation is not significant (H12). These findings suggest that while risk perception shapes psychological reliance on AI systems, it does not function as a primary mechanism driving investment success (Bashir et al., 2024). One possible explanation is that although investors become more dependent on AI when facing greater uncertainty, actual investment performance is influenced by

several external factors such as market volatility, portfolio diversification, execution quality and investment timing. Consequently, increased trust resulting from perceived risk does not automatically lead to superior financial outcomes. This diverges from prior studies emphasising risk as a barrier to technology adoption Bashir et al. (2024) and Halim and Pamungkas (2023) and highlights the adaptive risk attitudes of Generation Z in digitally evolving markets.

Trust in AI recommendation has a significant positive impact on investment performance, confirming trust as a critical behavioural driver of financial outcomes. When investors perceive AI systems as reliable, transparent, and consistent, they are more likely to rely on algorithmic insights, leading to improved decision quality and portfolio performance (Bashir et al., 2024). Financial advice may influence investor responses to AI recommendations (Bashir et al., 2024). For Generation Z, trust transforms AI from a mere information tool into a strategic decision-support partner, reducing cognitive burden and enhancing execution efficiency. This finding is consistent with trust theory, which proposes that trust reduces perceived uncertainty and increases individuals' willingness to rely on technological systems when making complex decisions. In AI-assisted investing, trust therefore serves not only as an antecedent of technology adoption but also as a behavioural mechanism that improves decision quality and financial performance. These findings support Maier et al. (2022) and extend TAM-based perspectives by positioning trust as a performance-enhancing mechanism rather than solely an adoption facilitator. Although some studies suggest trust does not always directly influence investment outcomes in developing markets, the present results indicate that within Indonesia's digital investment ecosystem, trust plays a central role in translating technological effectiveness into tangible financial benefits.

6 Conclusions

This study examined the influence of AI recommendation accuracy, investment goal orientation, technology readiness, and perceived risk on investment performance, with trust in AI recommendation serving as a mediating variable among Generation Z investors in Indonesia. The findings demonstrate that trust is a critical mechanism through which the effectiveness of AI-driven recommendations is translated into better investment performance. Investors are more likely to benefit from AI-based financial platforms when they perceive the recommendations as accurate and reliable, thereby strengthening their confidence in the technology. Among the antecedent variables, AI recommendation accuracy has the strongest influence on trust in AI recommendation, indicating that the credibility and consistency of algorithmic recommendations are essential for building user confidence. In addition, investment goal orientation and technology readiness have significant direct effects on investment performance, suggesting that investors who have clear financial objectives and are prepared to adopt digital technologies tend to achieve better investment outcomes. Although perceived risk significantly affects trust, it does not have a direct or indirect effect on investment performance. This finding implies that Generation Z investors are generally able to accommodate perceived uncertainty when they have sufficient confidence in AI-assisted investment platforms.

From a theoretical perspective, this study extends the application of the TAM by demonstrating that trust in AI recommendation functions as an important behavioural

mechanism connecting AI-related characteristics with investment performance. The results the growing body of literature on AI adoption in financial decision-making by showing that trust is not merely an outcome of technological acceptance but also a pathway through which AI-generated recommendations create value for investors. The findings of this study are consistent with the growing empirical evidence on investor behaviour and financial advisory mechanisms in digital finance (Bashir et al., 2023, 2024).

From a practical perspective, the findings suggest that developers of AI-based investment platforms should prioritise improving recommendation accuracy, transparency, and system reliability to strengthen investor trust. Financial institutions and fintech companies are also encouraged to enhance digital literacy and technology readiness among young investors through educational initiatives and user-oriented platform design. By fostering both technological capability and user trust, AI-enabled financial services can contribute more effectively to improving investment performance in emerging digital markets.

Declarations

All authors declare that they have no conflicts of interest.

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