Proceeding of the International Conference on Management, Entrepreneurship, and Business

E-ISSN: 3090-9155
P-ISSN: XXXX-XXXX

(Research) Article

The Influence of Robo Advisor, Financial Literacy, Risk Tolerance on Investment Behavior And Portfolio Performance

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Abstract: Research aims to explore the influence of robo-advisor usage, trust in artificial intelligence (AI), financial literacy, and risk tolerance on investment behavior and its impact on the portfolio performance of retail investors in Indonesia. This study applies a quantitative approach, collecting data from 100 respondents who use investment applications such as Bibit, Ajaib, and Bareksa through the distribution of structured questionnaires with a 5-point Likert scale. Data analysis was carried out using the Structural Equation Modeling (SEM) technique. The results indicate that the four independent variables robo-advisor usage, trust in AI, financial literacy, and risk tolerance significantly affect investment behavior, which in turn has a positive effect on portfolio performance. High trust in AI combined with strong financial literacy fosters more disciplined and rational investment behavior. These findings highlight the importance of effective AI technology integration, improving financial literacy, and managing risk preferences to enhance investment decision-making quality and financial well-being. The study contributes to behavioral finance literature and offers practical implications for fintech developers and policymakers in emerging markets.

Keywords: Financial literacy; Investment behavior; Risk tolerance; Robo advisor; Trust in AI.

Received: May 16, 2025
Revised: July 18, 2025
Accepted: September 18, 2025
Published: November 19, 2025
Curr. Ver.: November 19, 2025

1. Introduction

The development of financial technology (FinTech) in recent years has transformed the way society interacts with the world of investment. In the past, investment decisions largely depended on intuition, personal experience, or recommendations from traditional financial advisors; however, the process is now increasingly shaped by digital innovation. One of the most prominent innovations is the robo-advisor, an algorithm- and artificial intelligence (AI)-based platform that provides automated investment recommendations. The main advantage of robo-advisors lies in their ability to deliver services at low cost, efficiently, while still being tailored to investors' risk profiles and objectives (Alam & Achjari, 2024). Initially developed in the United States and Europe, this technology has, in recent years, begun to penetrate emerging markets, including Indonesia, which is currently promoting financial inclusion and expanding investment access (Ariyanti & Pangestuty, 2023)

The growth in the number of investors in Indonesia shows an encouraging trend. Based on data from the Indonesian Central Securities Depository (KSEI), the number of retail investors surpassed 10 million in 2022, a sharp increase compared to previous years. However, this rise in investor numbers has not been matched by improvements in financial literacy. Capital market literacy remains far behind banking literacy (Ariyanti & Pangestuty, 2023). Limited financial understanding makes many retail investors vulnerable to decision-making errors, such as herding effects, overconfidence, or loss aversion (Shahzad et al., 2024). In this context, robo-advisors can help mitigate such biases by providing more objective, data-driven recommendations (Oehler, Horn, & Wendt, 2022).

Nevertheless, public acceptance of robo-advisors (X1) still faces challenges. Several studies have found evidence of algorithm aversion, where investors are hesitant to rely on algorithmic recommendations even when proven to outperform manual decisions (Filiz, Judek, & Spiwoks, 2022; Liu et al., 2023). Psychological factors also play a role: overconfident investors may dismiss robo-advisor suggestions, while others may over-rely on the technology despite having limited financial knowledge (Piehlmaier, 2022)This underscores that the success of robo-advisors depends not only on technological capabilities but also on investor behavior in responding to the information provided.

In addition to behavioral factors, trust in AI (X2) also emerges as a critical variable in determining the extent to which investors are willing to adopt robo-advisors. Such trust encompasses the belief that the system operates transparently, securely, and reliably. Without trust, investors are likely to remain skeptical about relying on automated technologies. Conversely, with higher trust levels, adoption and sustained use are more likely (Amalia & Subagyo, 2024; Pinandhito et al., 2025). Other studies emphasize that e-trust often serves as a bridge determining the success of digital innovations, including robo-advisors (Amalia & Subagyo, 2024; Alam & Achjari, 2024).

Moreover, financial literacy (X3) remains a fundamental foundation. Investors with strong financial literacy are better able to assess the relevance of recommendations, utilize technological features, and develop portfolio strategies aligned with their goals (Lusardi & Mitchell, 2023; Alam & Achjari, 2024). Risk tolerance (X4) also plays a critical role in investment decision-making. Investors with high risk tolerance tend to build more aggressive portfolios, while risk-averse individuals generally opt for conservative strategies (Grable & Lytton, 1999; Lai & Chow, 2023). However, recent studies indicate that risk assessment questionnaires used by robo-advisors often produce less personalized recommendations, particularly in the Asia-Pacific region (Lai & Chow, 2023). The most significant finding of this study is the identification of six major clusters: investor behavior during times of crisis; behavioral finance; herding and risk-taking concepts; psychological and cognitive decisions; emotions and decision-making; and the performance of stocks (Ikram et al., 2023)

The interrelationship among these factors ultimately converges on two main outcomes: investment behavior (M) and portfolio performance (Y1). Rational, disciplined investment behavior, supported by financial literacy and trust in technology, is believed to improve long-term portfolio outcomes. In contrast, biased or uncertain behavior poses risks of diminished investment performance. Some studies show that robo-advisor-managed portfolios are even more stable in the face of market volatility compared to manual investor decisions, as evidenced during the COVID-19 crisis (Liu et al., 2023).

Although numerous studies have highlighted robo-advisors, financial literacy, or risk tolerance, most have been conducted in developed countries with higher digital literacy levels and more mature financial infrastructures (Oehler et al., 2022; (Filiz et al., 2022)). Research integrating the roles of robo-advisors, trust in AI, financial literacy, and risk tolerance in shaping investment behavior (M) and their impact on portfolio performance (Y1) within the context of emerging markets such as Indonesia remains scarce (Banerjee, 2024; Grealish & Kolm, 2021).

Based on this gap, this study aims to provide a more comprehensive understanding of how these four factors interact in influencing investment behavior and portfolio outcomes. The specific objectives are: (1) to examine the role of robo-advisors in shaping investment behavior; (2) to assess the influence of trust in AI on the adoption and sustained use of robo-advisors; (3) to analyze the contribution of financial literacy to decision-making and portfolio performance; (4) to evaluate the role of risk tolerance in investment behavior and outcomes; and (5) to provide a holistic view of the impact of these four factors on the investment behavior and portfolio performance of retail investors in Indonesia.

From the above discussion, it is clear that there remains a research gap to be addressed. Most previous studies examined robo-advisors, financial literacy, or risk tolerance separately, and were predominantly conducted in developed countries with more advanced financial infrastructures and higher digital literacy levels (Oehler et al., 2022; Filiz et al., 2022). Research that specifically integrates robo-advisors, trust in AI, financial literacy, and risk tolerance in shaping investment behavior and their effects on portfolio performance in developing countries such as Indonesia is still very limited (Banerjee, 2024; Grealish & Kolm, 2021).

Therefore, this study presents novelty in three main aspects: (1) integrating four key factors (robo-advisors, trust in AI, financial literacy, and risk tolerance) into a single comprehensive model; (2) positioning trust in AI as an independent variable directly influencing investment behavior; and (3) highlighting the context of a developing country, namely Indonesia, which is experiencing rapid growth in the number of retail investors but still faces diverse levels of financial literacy and technological trust.

Beyond this novelty, the study also carries broad significance. For academics, it enriches the literature on behavioral finance and technology adoption by introducing a more integrative model. For fintech developers, the findings can serve as valuable input in designing robo-advisors that are more credible, adaptive, and aligned with investors' risk profiles. For regulators and educators, the study provides empirical evidence that can inform investor protection policies and more targeted financial literacy programs. Equally important, for retail investors, it offers practical insights on how technology can be leveraged to enhance investment decision-making quality while improving portfolio performance.

In conclusion, this study aims to empirically test the influence of robo-advisor adoption, trust in AI, financial literacy, and risk tolerance on investment behavior and portfolio performance of retail investors in Indonesia. The findings are expected to contribute both theoretically and practically, while supporting the creation of a more inclusive, sustainable, and competitive Indonesian capital market in the digital era.

2. Literature Review

The rapid development of digital technology has reshaped the global financial system and given rise to investment services that are both more efficient and inclusive. One of the most relevant innovations is robo-advisors, algorithm- and artificial intelligence (AI)-based platforms that provide automated investment recommendations. However, the adoption of this technology is not solely dependent on system sophistication, but is also influenced by trust in AI, financial literacy, and investors' attitudes toward risk. This literature review explores the role of these four factors in shaping investment behavior and their implications for portfolio performance, particularly in Indonesia, which is experiencing a significant surge in retail investors.

Robo-Advisor

A robo-advisor is an AI-based financial service that provides automated investment recommendations using algorithms (Choi & Ngo-Ye, 2023). In Indonesia, robo-advisors are gaining popularity through applications such as Bibit and Bareksa, which offer low-cost and user-friendly access to investments (Ariyanti & Pangestuty, 2023). Adoption of robo-advisors is strongly influenced by users' trust and their willingness to continue using the service (Alam & Achjari, 2024a). Empirical studies show that robo-advisors can outperform human investors during periods of market turbulence, such as the COVID-19 pandemic (Liu et al., 2023). However, some investors still experience algorithm aversion, or reluctance to fully rely on machine-based decisions (Filiz et al., 2022).

Trust in AI (E-Trust)

Trust in AI systems is defined as the belief that these systems are competent, honest, and act with good intentions in delivering services (Xie et al., 2020). Trust has been shown to be a critical factor influencing the adoption of robo-advisors by retail investors (Oehler et al., 2022). In Indonesia, research indicates that e-trust mediates the relationship between robo-advisor features and investment decision-making (Amalia & Subagyo, 2024). Other studies confirm that e-trust strengthens the role of robo-advisors in shaping retail investors' intentions (Alam & Achjari, 2024b). System performance has also been found to positively influence user trust (Maier et al., 2022). Moreover, investors' trust in AI tends to evolve through repeated interactions with robo-advisors (Trinh et al., 2025).

Financial Literacy

Financial literacy is understood as an individual's ability to comprehend basic financial concepts and make appropriate decisions related to money management (Broekema & Kramer, 2021). This knowledge encompasses topics such as compound interest, inflation, risk diversification, and investment instruments (Lusardi & Mitchell, 2023). The level of financial literacy plays a crucial role in reducing vulnerability to investment fraud (Xiao et al., 2022). In Indonesia, financial literacy has been shown to significantly influence the investment decisions of the younger generation (Fatin & Juwita, 2023). In Europe, it is even regarded as a primary predictor of the adoption of robo-advisory services (Aristei & Gallo, 2025.) Other studies further emphasize that strong financial literacy enables investors to make rational decisions, even during times of crisis (Mahat & Lau, 2023).

Risk Tolerance

Risk tolerance is defined as the extent to which an individual is willing to accept uncertainty in financial decision-making (Kuzniak et al., 2015) The Grable & Lytton instrument is widely used to quantitatively measure investors' risk preferences (Grable & Lytton, 2019). Risk tolerance has been shown to exert a significant influence on investors' portfolio choices (Amponsah et al., 2025).Research further indicates that the level of risk tolerance also determines the extent to which individuals are comfortable utilizing robo-advisors (Lai & Chow, 2023). In the Indonesian context, this factor, together with financial literacy, has been found to affect individual investment decisions (Fatin & Juwita, 2023) Recent studies also confirm that risk tolerance is closely associated with portfolio performance among investors who employ robo-advisory services (Hasanudin, 2025)

Investment Behavior

Investment behavior refers to the way individuals make decisions in allocating assets, often shaped by both psychological and rational factors (Shahzad et al., 2024). Financial literacy has been proven to directly influence investment behavior, particularly in enabling informed decision-making (Mahat & Lau, 2023). Other studies suggest that investment behavior is also affected by risk tolerance, especially when investors face market uncertainty (Yanti & Endri, 2024). The adoption of financial technologies, including robo-advisors, further reinforces the investment behavior patterns of younger generations (Pinandhito et al., 2025). Thus, investment behavior can be understood as the outcome of interactions between cognitive, emotional, and technological factors.

Portfolio Performance

Portfolio performance is generally measured by the extent to which an investment is able to generate optimal returns with controlled risks (Hasanudin, 2025) One of the most commonly used measures is the Sharpe ratio, which evaluates the balance between return and risk (Hasanudin, 2025) In Indonesia, the use of robo-advisors has been shown to enhance portfolio diversification for retail investors (Putra & Sari, 2024). Other studies demonstrate that the sustained use of robo-advisors is influenced by investors' perceptions of improvements in their portfolio performance (Alam & Achjari, 2024c). Empirical evidence further reveals that robo-advisory algorithms can assist investors in avoiding emotional decisions that may lead to financial losses (Liu et al., 2023).

Hypotesys Development

This study proposes a conceptual model linking robo-advisor usage, trust in AI, financial literacy, risk tolerance, and investment behavior to portfolio performance. Financial literacy and risk tolerance are emphasized as key determinants of investment choices (Lusardi & Mitchell, 2023), while portfolio performance represents the ultimate measure of success (Hasanudin, 2025).

Robo-Advisors and Investment Behavior

The concept of robo-advisors can be understood through the Technology Acceptance Model (Davis, 1989), which highlights perceived usefulness and ease of use, and through behavioral finance perspectives that suggest robo-advisors reduce biases such as loss aversion, overconfidence, and herding ((Ben David et al., 2021). Supported by Simon's (1957) theory of bounded rationality, robo-advisors help investors make more rational choices under limited information, with evidence showing greater portfolio stability during market volatility, including the COVID-19 pandemic (Liu et al., 2023). In Asia, adoption continues to grow but faces challenges of trust and understanding (Lai & Chow, 2023), while in Indonesia millennials and Gen Z dominate usage of platforms such as Bibit and Ajaib despite barriers like algorithm aversion (Amalia & Subagyo, 2024; Filiz, Judek, & Spiwoks, 2022). Overall, robo-advisors attract young investors due to accessibility (Ariyanti & Pangestuty, 2023; Alam & Achjari, 2024), yet their real influence on retail investment behavior in Indonesia requires further investigation.

H1: The use of robo-advisors has a positive effect on investment behavior.

Trust in AI and Investment Adoption

Trust in AI, as explained by the Trust in Technology Theory (Gefen, Karahanna, & Straub, 2003), emphasizes not only usefulness but also perceptions of security, transparency, and reliability, making e-trust crucial in robo-advisors where issues of privacy, fairness, and platform reputation matter (Frai, 2021). Empirical studies in Indonesia confirmed that e-trust mediates the link between robo-advisor features, user satisfaction, and continued usage (Pinandhito et al., 2025; Alam & Achjari, 2024), while global evidence highlights transparency as a key driver of trust in AI (Xie et al., 2021). However, overreliance on technology may weaken critical judgment (Frai, 2021), and adoption remains limited in Indonesia due to relatively low levels of digital trust (Amalia & Subagyo, 2024).

H2: Trust in AI has a positive effect on investment behavior.

Financial Literacy and Investment Decision-Making

Financial literacy, as defined by Financial Literacy Theory (Lusardi & Mitchell, 2023), covers financial management, investment, and risk management, serving as a cognitive tool that reduces biases and enhances investor self-efficacy. In Indonesia, literacy levels remain low despite growing market participation (Ariyanti & Pangestuty, 2023), leaving retail investors vulnerable to herding and suboptimal decisions (Shahzad et al., 2024). Prior studies further show that higher literacy strengthens robo-advisor effectiveness (Amalia & Subagyo, 2024) andunderscoring its central role in investment quality.

H3: Financial literacy has a positive effect on investment behavior.

Risk Tolerance and Portfolio Performance

Risk tolerance, a fundamental determinant of investment behavior explained by Prospect Theory (Kahneman & Tversky, 1979), reflects investors' greater sensitivity to losses than gains and is commonly measured using the Grable and Lytton (2019) scale. It is influenced by psychological, demographic, and economic factors, with studies showing its impact on both portfolio choices and outcomes: in Indonesia, Kurnijanto et al. (2025) found that it significantly shapes investment preferences, while Liu et al. (2023) confirmed that risk-aligned portfolios are more resilient during crises. However, Lai and Chow (2023) observed that risk assessments applied by robo-advisors in Asia remain simplistic and often fail to capture investors' true profiles. These findings highlight that although risk tolerance is central to investment success, current measurement methods, particularly in emerging markets, may still be inadequate.

H4: Risk tolerance has a positive effect on investment behavior.

Integrated Influence on Investment Behavior and Portfolio Outcomes

Investment decisions are shaped by psychological, cognitive, and technological factors (Kahneman & Tversky, 1979; Venkatesh et al., 2003), with evidence showing that trust, financial literacy, and risk tolerance strongly influence the adoption and effectiveness of robo-advisors (Alam & Achjari, 2024; Pinandhito et al., 2025). While robo-advisors enhance consistency in investment strategies, behavioral biases remain a challenge (Liu et al., 2023; Shahzad et al., 2024). In Indonesia, research on how these variables jointly affect portfolio performance is still limited, highlighting the need for deeper investigation.

H5: Investment behavior has a positive effect on portfolio performance.

Robo-Advisors and Portfolio Performance

Robo-advisors increasingly play a role in shaping portfolio outcomes through automated diversification and rebalancing. Liu et al. (2023) showed that during the COVID-19 market downturn, robo-advisor portfolios demonstrated more stability than those managed by individual investors. Similarly, Lai and Chow (2023) highlighted that robo-advisors can enhance efficiency, although many platforms still rely on relatively simple risk assessment methods. In Indonesia, Amalia and Subagyo (2024) found that robo-advisor usage among young investors has encouraged better portfolio discipline, even though the adoption rate remains relatively low.

Robo-advisors support portfolio performance by encouraging discipline and reducing emotional biases, yet their effectiveness is conditioned by investor trust and familiarity with the system.

H6: The use of robo-advisors has a positive effect on portfolio performance.

Trust in Artificial Intelligence (AI) and Portfolio Performance

Trust is a central element in the success of AI-driven financial tools. Alam and Achjari (2024) emphasized that trust in AI strengthens investors' willingness to follow automated advice, which in turn contributes to improved investment outcomes. Pinandhito et al. (2025) also found that e-trust mediates the relationship between robo-advisor features and investor satisfaction, indicating that confidence in AI plays a decisive role in determining portfolio results. However, studies also caution that low levels of digital trust in Indonesia remain a significant barrier (Amalia & ., 2024). Trust in AI is not only a prerequisite for adoption but also directly influences portfolio outcomes by increasing investor confidence in following algorithm-based recommendations.

H7: Trust in AI has a positive effect on portfolio performance.

Financial Literacy and Portfolio Performance

Financial literacy is widely recognized as an essential driver of effective investment decision-making. Ariyanti and Pangestuty (2023) reported that in Indonesia, financial literacy in the capital market remains low, despite the rapid increase in retail investors. This gap often leads to suboptimal investment outcomes. Amalia and Subagyo (2024) found that higher financial literacy strengthens the effectiveness of robo-advisors, as literate investors are better equipped to evaluate algorithmic recommendations. Globally, Liu et al. (2023) confirmed that financial knowledge enables investors to maintain consistent portfolio strategies, even in times of market turbulence. Stronger financial literacy provides investors with the ability to align technology use with long-term financial goals, ultimately improving portfolio performance.

H8: Financial literacy has a positive effect on portfolio performance.

Risk Tolerance and Portfolio Performance

Risk tolerance is a crucial determinant of portfolio choices and outcomes. Lai and Chow (2023) found that risk assessment practices in Asian robo-advisors remain basic and do not always reflect investors' true preferences. In the Indonesian context, Kurnijanto et al. (2025) showed that risk tolerance significantly shapes investment preferences and long-term results, with high-risk investors tending to select more aggressive portfolios. Liu et al. (2023) further confirmed that portfolios adjusted to risk tolerance levels are generally more resilient during financial crises.

Risk tolerance ensures that portfolios are consistent with investor comfort levels, and when well-assessed, it enhances resilience and long-term performance.

H9: Risk tolerance has a positive effect on portfolio performance.

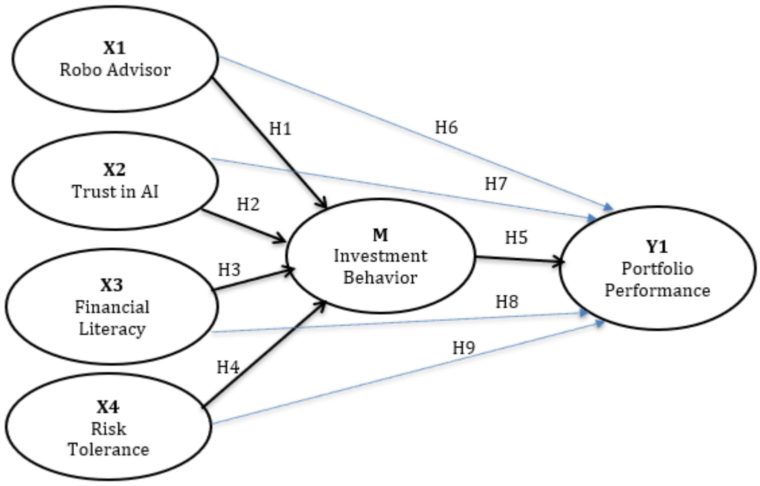

Figure 1. Conceptual Framework.
Source: Results of data processing and using ms.word,2025

This research framework shows how technology (Robo-Advisors), trust (Trust in AI), knowledge (Financial Literacy), and risk attitude (Risk Tolerance) influence Investment Behavior. Investment Behavior acts as a mediator, meaning it connects those four factors to Portfolio Performance. In simple terms: the way investors use technology, trust AI, understand finance, and deal with risk will shape how they invest. These behaviors, in turn, affect how well their investment portfolios perform.

3. Research Method

This study adopts a quantitative explanatory research design to empirically examine the relationships between robo-advisor usage, trust in artificial intelligence (AI), financial literacy, risk tolerance, investment behavior, and portfolio performance. A quantitative approach is appropriate since the variables under investigation cannot be manipulated experimentally, and the focus is on testing causal relationships using survey data (Hair et al., 2019). Data were collected through an online questionnaire distributed to retail investors in Indonesia who use robo-advisor platforms such as Bibit, Bareksa, and Ajaib, with responses measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The population of this research consists of retail investors in Indonesia who have used robo-advisors for at least six months. A purposive sampling technique was employed to ensure respondents meet specific criteria relevant to the study (Fatin & Juwita, 2023).

A total of 100 valid responses were obtained, representing a diverse age group ranging from below 20 years old to above 50 years old, which reflects the generational diversity of robo-advisor users in Indonesia (Amalia & Subagyo, 2024). This sample size is considered adequate for Structural Equation Modeling with Partial Least Squares (SEM-PLS), which generally requires 5–10 observations per indicator (Hair et al., 2019). The questionnaire items were adapted from validated constructs in prior studies. Indicators for robo-advisor usage were drawn from Choi & Ngo-Ye (2023) and Liu et al. (2023), while trust in AI (e-trust) followed the frameworks of Xie et al. (2020) and Oehler et al. (2022). Financial literacy was measured using concepts established by Lusardi & Mitchell (2023), and risk tolerance was assessed with the Grable & Lytton (2019) scale.

Investment behavior was measured based on the works of Shahzad et al. (2024) and Yanti & Endri (2024), while portfolio performance relied on indicators related to risk-return balance and goal achievement, adapted from Hasanudin (2025) and Putra & Sari (2024). Data analysis was conducted using SEM-PLS with SmartPLS 4.0, chosen for its robustness in handling non-normal data and relatively small sample sizes (Hair et al., 2019). The analysis followed three steps: (1) descriptive analysis to profile respondents and summarize responses; (2) measurement model evaluation (outer model), which assessed convergent validity, discriminant validity, and construct reliability; and (3) structural model evaluation (inner model), which examined R-square values, predictive relevance (Q^2), and path significance through bootstrapping. Furthermore, a mediation test was conducted to assess whether investment behavior mediates the effects of robo-advisor usage, trust in AI, financial literacy, and risk tolerance on portfolio performance (Alam & Achjari, 2024; Pinandhito et al., 2025). Ethical considerations were carefully addressed. Participation was voluntary, informed consent was obtained, and respondents' identities were kept confidential. No sensitive financial information was collected beyond their general investment behavior and perceptions (Amponsah et al., 2025).

4. Results and Discussion

Table 1. Investor Demographics and Behavioral Context.

Age, Occupation, Investment Experience, Income	Male	Female	Grand Total
< 20 Years	5	7	12
Student	5	7	12
< IDR 5 Million	5	7	12
< 1 Year	4	7	11
1 - 3 Years	1		1
> 50 Years	2	3	5
Civil Servant (PNS/ASN)		1	1
> 20 Million		1	1
> 3 Years		1	1
Private Employee	1		1
IDR 10 - 20 Million	1		1
> 3 Years	1		1

Retired		1	1
< 5 Million		1	1
1 - 3 Years		1	1
Unemployed	1		1
< 5 Million	1		1
> 3 Years	1		1
Entrepreneur		1	1
IDR 5 - 10 Million		1	1
1 - 3 Years		1	1
20 - 30 Years	21	37	58
Civil Servant (PNS/ASN)	3	1	4
IDR 10 - 20 Million	1		1
> 3 Years	1		1
IDR 5 - 10 Million	2	1	3
1 - 3 Years	2	1	3
Private Employee	2	5	7
< IDR 5 JMillion	1	2	3
< 1 Year		2	2
1 - 3 Years	1		1
IDR 10 - 20 Million		1	1
> 3 Years		1	1
IDR 5 - 10 Million	1	2	3
1 - 3 Years	1	2	3
Freelancer	1	1	2
IDR 10 - 20 Million	1		1
> 3 Years	1		1
IDR 5 - 10 Million		1	1
1 - 3 Years		1	1
Student	12	25	37
< IDR 5 Million	9	23	32
< 1 Year	4	12	16
1 - 3 Years	5	11	16
> IDR 20 Million	1		1
< 1 Year	1		1
IDR 5 - 10 Million	2	1	3
< 1 Year	1		1
1 - 3 Years	1	1	2
< IDR 5 Million		1	1
< 1 Year		1	1
Professional (Doctor, Lawyer, Consultant, etc.)	1	1	2
IDR 10 - 20 Million		1	1
1 - 3 Years		1	1
IDR 5 - 10 Million	1		1
> 3 Years	1		1
Unemployed	1		1
IDR < 5 Million	1		1
< 1 Year	1		1

Entrepreneur	1	4	5
IDR < 5 Million		1	1
1 - 3 Years		1	1
IDR > 20 Million		1	1
1 - 3 Years		1	1
IDR 10 - 20 Million	1	1	2
< 1 Year		1	1
> 3 Years	1		1
IDR 5 - 10 Million		1	1
> 3 Years		1	1
31- 40 Years	6	8	14
Civil Servant (PNS/ASN)	1		1
IDR 10 - 20 Million	1		1
> 3 Years	1		1
Private Employee		2	2
IDR 10 - 20 Million		1	1
> 3 Years		1	1
IDR 5 - 10 Million		1	1
1 - 3 Years		1	1
Freelancer	2	2	4
IDR 10 - 20 Million	1	2	3
> 3 Years	1	2	3
IDR 5 - 10 Million	1		1
1 - 3 Years	1		1
Professional (Doctor, Lawyer, Consultant, etc.)	3		3
> IDR 20 Million	1		1
> 3 Years	1		1
IDR 10 - 20 Million	1		1
1 - 3 Years	1		1
IDR 5 - 10 Million	1		1
> 3 Years	1		1
Entrepreneur		4	4
> IDR 20 Million		1	1
> 3 Years		1	1
IDR 10 - 20 Million		2	2
> 3 Years		1	1
1 - 3 Years		1	1
IDR 5 - 10 Million		1	1
1 - 3 Years		1	1
41 - 50 Years	5	6	11
House Wife		2	2
< IDR 5 Million		2	2
1 - 3 Years		2	2
Civil Servant (PNS/ASN)		1	1
IDR 5 - 10 Million		1	1
1 - 3 Years		1	1
Private Employee	4	1	5

IDR 10 - 20 Million	2		2
> 3 Years	2		2
IDR 5 - 10 Million	2	1	3
1 - 3 Years	2	1	3
Farmer	1		1
IDR 10 - 20 Million	1		1
< 1 Year	1		1
Professional (Doctor, Lawyer, Consultant, etc.)		1	1
> IDR 20 Million		1	1
1 - 3 Years		1	1
Entrepreneur		1	1
> IDR 20 Million		1	1
> 3 Years		1	1
Grand Total	39	61	100

Source: Premier Data and using Excel, 2025

The demographic profile of respondents reveals a clear concentration of young investors, particularly those between 20 and 30 years old, with limited investment experience and relatively modest income levels. This composition underscores the emergence of millennials and Gen Z as the primary users of robo-advisory services in Indonesia. Their dominant presence in the sample reflects a generation that is highly adaptive to digital tools but still developing financial maturity. Table 1 supports this view, showing that women comprise the majority (61%), and most respondents earn less than IDR 5 million monthly.

The dominance of younger, early-stage investors provides an important context for interpreting behavioral outcomes. Their reliance on robo-advisors is not merely a matter of convenience but a necessity, as limited financial literacy and risk management experience often require technological guidance. These findings resonate with H1, which posits that robo-advisors influence investment behavior by instilling greater discipline among less experienced investors.

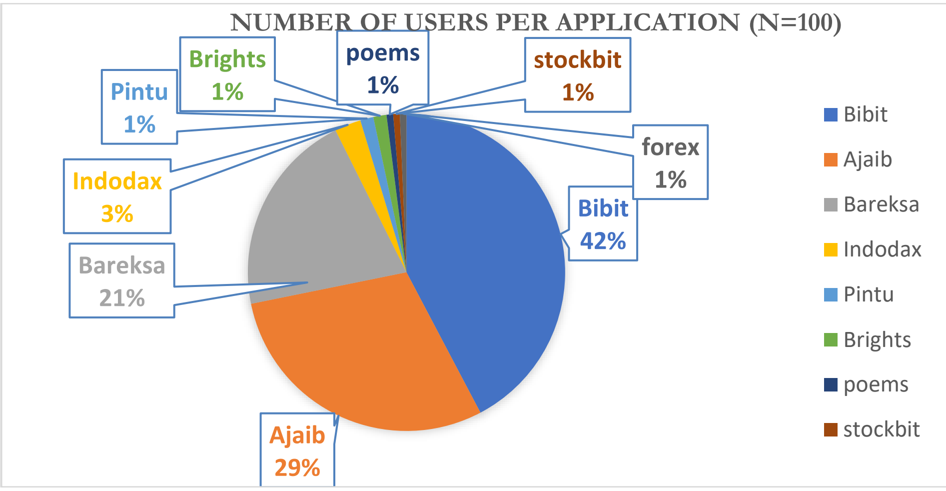

Figure 2. Distribution of Investment Applications
Source: Results of data processing and using Excel,2025

Patterns of technology adoption also emerge from respondents' choice of investment platforms. Figure 2 demonstrates that Bibit holds a commanding share (42%), followed by Ajaib (29%) and Bareksa (21%), while other applications remain marginal. This concentration suggests that the market rewards platforms that offer ease of use, transparency, and educational features. Such preferences highlight that investors are not merely seeking investment access but also guidance and reassurance, which robo-advisors are designed to provide. This aligns with the Technology Acceptance Model (TAM), where simplicity and perceived usefulness are central to adoption. By choosing platforms that emphasize clarity and low barriers to entry, investors reveal a preference for structure supporting the premise of H1, that robo-advisors shape investment behavior by standardizing decision-making for beginners.

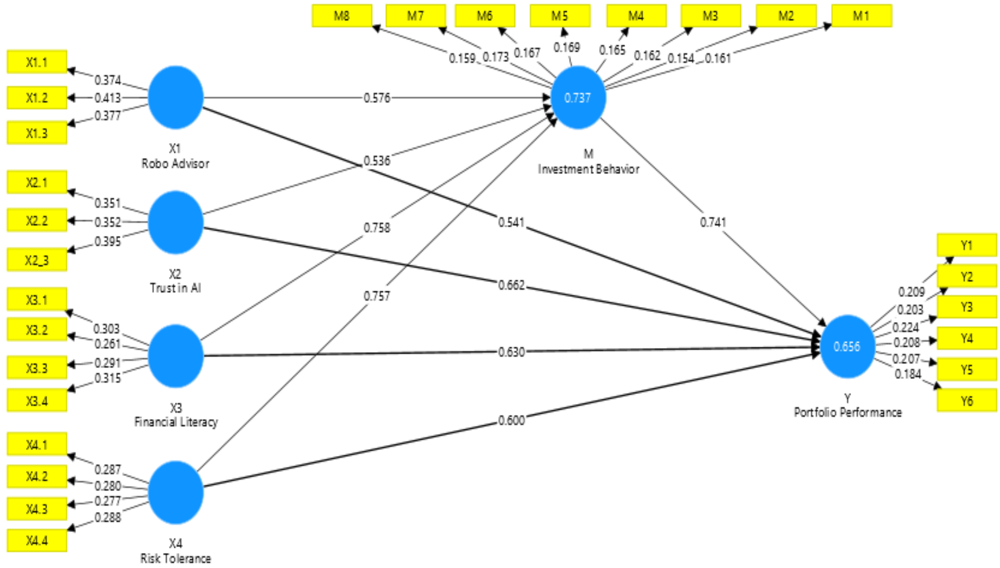

Figure 3. Outer model test results.
Source: Results of data processing and using Smart PLS, 2025

The structural model Figure 3 highlights how technological, cognitive, and psychological factors shape portfolio performance, with Investment Behavior acting as the key mediator. The model explains a large share of variance in both outcomes (73.7% for Investment Behavior and 65.6% for Portfolio Performance), confirming its strong explanatory power (Hair et al., 2021). Robo-advisor use significantly improves investment behavior but has little direct impact on performance, showing that technology works mainly through behavioral channels (Lai & Chow, 2023). Trust in AI, while less influential on behavior, strongly enhances performance, supporting the view that trust enables effective use of digital tools (Amalia & Subagyo, 2024). Financial literacy and risk tolerance both play major roles in shaping behavior, though their direct effects on performance are limited, consistent with earlier findings that knowledge and attitudes matter most when translated into disciplined actions (Lusardi & Mitchell, 2023). The strongest effect is observed from Investment Behavior to Portfolio Performance, underscoring its central role in linking literacy, risk, technology, and trust to investment success. Finally, the measurement quality is confirmed, as all indicators exceed recommended thresholds, ensuring reliability of the constructs.

Tabel 2. Descriptive Statistics of Research Variables

	Mean	Standard deviation
Investment Behavior	-0.000	1.000
Robo Advisor	0.000	1.000
Trust in AI	-0.000	1.000
Financial Literacy	0.000	1.000
Risk Tolerance	-0.000	1.000
Portfolio Performance	0.000	1.000

Source: Results of data processing and using Smart PLS, 2025

Descriptive statistics in Table 2 present standardized values for the study constructs Investment Behavior, Robo-Advisor, Trust in AI, Financial Literacy, Risk Tolerance, and Portfolio Performance with mean values centered at zero and identical standard deviations of 1.000, reflecting the standardization process conducted in SmartPLS (2025). This transformation, a common practice in PLS-SEM (Hair et al., 2021), normalizes the data and ensures comparability across constructs, preventing differences in measurement scales from distorting structural relationships. By rescaling variance to a common unit, the coefficients obtained in the structural model more accurately represent relational strength rather than variability in the raw data, thereby enhancing the reliability of hypothesis testing. Conceptually, these statistics highlight methodological rigor, ensuring that subsequent findings such as the influence of Financial Literacy and Risk Tolerance on Investment Behavior or the role of Trust in AI on Portfolio Performance reflect robust structural interplay rather than artifacts of measurement error.

Table 3. Outer Loading

Variable	Indicator	Outer Loading	Interpretation
Investment Behavior	M1	0.780	Valid
	M2	0.772	Valid
	M3	0.805	Valid
	M4	0.785	Valid
	M5	0.815	Valid
	M6	0.703	Valid
	M7	0.772	Valid
	M8	0.710	Valid
Robo Advisor	X1_1	0.840	Valid
	X1_2	0.901	Valid
	X1_3	0.832	Valid
Trust In Ai	X2_1	0.891	Valid
	X2_2	0.919	Valid
	X2_3	0.919	Valid
Financial Literacy	X3_1	0.845	Valid
	X3_2	0.876	Valid
	X3_3	0.870	Valid
	X3_4	0.834	Valid
Risk Tolerance	X4_1	0.871	Valid
	X4_2	0.873	Valid
	X4_3	0.893	Valid
	X4_4	0.899	Valid
Portfolio Performance	M	0.786	Valid
	Y1	0.801	Valid
	Y3	0.837	Valid
	Y4	0.845	Valid
	Y5	0.846	Valid
	Y6	0.728	Valid

Source: Results of data processing and using Smart PLS, 2025

The outer loading analysis demonstrates that all indicators exceed the recommended threshold of 0.70, ranging from 0.703 to 0.919, thereby confirming convergent validity (Hair et al., 2021). For Investment Behavior, loadings span 0.703–0.815, while Robo-Advisor (X1) shows consistently high values (0.832–0.840), and Trust in AI (X2) records the strongest loading (0.919), highlighting the importance of transparency and credibility in shaping trust. Financial Literacy (X3: 0.834–0.876), Risk Tolerance (X4: 0.873–0.899), and Portfolio Performance (Y: 0.728–0.846) also display robust validity, with long-term orientation and return stability emerging as key performance indicators. Complementary measures confirm reliability, as Cronbach's Alpha values for all constructs exceed 0.80 (Nunnally & Bernstein, 1994), Composite Reliability (CR) values surpass 0.70 with most above 0.85, and Average Variance Extracted (AVE) results consistently exceed 0.50 (Fornell & Larcker, 1981). Collectively, these results establish strong reliability and convergent validity, providing a solid methodological basis for subsequent discriminant validity testing and structural model evaluation.

Table 4. Contruct Reability and Validity.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Investment Behavior	0.897	0.898	0.918	0.584
Robo Advisor	0.820	0.826	0.893	0.736
Trust in AI	0.897	0.910	0.935	0.828
Financial Literacy	0.879	0.881	0.917	0.734
Risk Tolerance	0.907	0.907	0.935	0.781
Portfolio Performance	0.893	0.897	0.919	0.653

Source: Results of data processing and using Smart PLS, 2025

The results in Table 4 confirm that all constructs demonstrate strong reliability and validity, providing a solid basis for the structural analysis. Cronbach's Alpha and Composite Reliability values for all variables exceeded 0.80, indicating internal consistency, with particularly high scores for Trust in AI and Risk Tolerance (0.935), consistent with prior validations of risk-tolerance and trust measures (Grable & Lytton, 2019; Oehler, Horn, & Wendt, 2022; Lai & Chow, 2023). Convergent validity was also established, as all AVE values surpassed the 0.50 threshold (Fornell & Larcker, 1981), with Trust in AI achieving the highest (0.828) and Investment Behavior the lowest (0.584), reflecting the multidimensional nature of investor trust (Xie et al., 2020) and the complexity of behavioral constructs (Shahzad, Khan, & Malik, 2024). Overall, these results confirm that robo-advisor usage, trust in AI, financial literacy, and risk tolerance are reliably measured, ensuring that the structural model is methodologically sound and aligned with prior evidence on the interplay of technological adoption, knowledge, and risk preferences in shaping investment outcomes (Lusardi & Mitchell, 2023; Liu et al., 2023).

Table 5. Discriminant Validity Fornell-Larcker.

	Investment Behavior	Robo Advisor	Trust in AI	Financial Literacy	Risk Tolerance	Portfolio Performance
Investment Behavior	0.764					
Robo Advisor	0.576	0.858				
Trust in AI	0.537	0.637	0.910			
Financial Literacy	0.759	0.366	0.442	0.857		
Risk Tolerance	0.757	0.452	0.488	0.682	0.884	
Portfolio Performance	0.746	0.536	0.657	0.637	0.608	0.808

Source: *Results of data processing and using Smart PLS, 2025*

Presents the results of discriminant validity testing using the Fornell-Larcker criterion. According to Fornell and Larcker (1981), discriminant validity is established when the square root of the Average Variance Extracted (AVE) for each construct is greater than its correlations with other constructs. The findings demonstrate that all constructs in this study meet this criterion. For example, Investment Behavior shows a value of 0.764 on the diagonal, which is higher than its correlations with Robo Advisor (0.576) and Trust in AI (0.537). Likewise, Risk Tolerance (0.884) and Trust in AI (0.910) both display values substantially higher than their inter-construct correlations. This indicates that each construct is empirically distinct and does not overlap excessively with others.

These results confirm that the measurement model is conceptually sound, with each construct representing a unique theoretical dimension. In practice, this means that robo-advisor usage, trust in AI, financial literacy, risk tolerance, investment behavior, and portfolio performance are empirically distinguishable. Such findings align with Oehler, Horn, and Wendt (2022), who emphasized the importance of clearly separating investor characteristics such as literacy, trust, and risk attitudes to avoid bias in behavioral finance models. The Fornell-Larcker results in this study therefore strengthen the validity of the conceptual framework and justify further testing at the structural level.

Table 6. Discriminant Validity HTMT.

	Heterotrait-monotrait ratio (HTMT)
Robo Advisor <-> Investment Behavior	0.671
Trust in AI <-> Investment Behavior	0.594
Trust in AI <-> Robo Advisor	0.741
Financial Literacy <-> Investment Behavior	0.846
Financial Literacy <-> Robo Advisor	0.426
Financial Literacy <-> Trust in AI	0.491
Risk Tolerance <-> Investment Behavior	0.839
Risk Tolerance <-> Robo Advisor	0.527
Risk Tolerance <-> Trust in AI	0.542
Risk Tolerance <-> Financial Literacy	0.760
Portfolio Performance <-> Investment Behavior	0.828
Portfolio Performance <-> Robo Advisor	0.629
Portfolio Performance <-> Trust in AI	0.736
Portfolio Performance <-> Financial Literacy	0.709
Portfolio Performance <-> Risk Tolerance	0.667

Source: Results of data processing and using Smart PLS, 2025

Table 6 reports discriminant validity results using the Heterotrait-Monotrait Ratio (HTMT), which has been recommended as a more stringent criterion for assessing construct distinctiveness (Henseler, Ringle, & Sarstedt, 2015). A value below 0.90 is generally considered acceptable to confirm discriminant validity. The results indicate that all HTMT values fall within the acceptable range. For instance, the HTMT between Investment Behavior and Financial Literacy is 0.846, and between Investment Behavior and Risk Tolerance is 0.839. While relatively high, these values remain below the 0.90 threshold, thus maintaining discriminant validity. On the other hand, constructs such as Financial Literacy and Robo Advisor (0.426) and Trust in AI and Financial Literacy (0.491) display lower HTMT values, reinforcing that these dimensions are conceptually well separated. The HTMT results provide additional support for the discriminant validity already established through the Fornell-Larcker test. This dual confirmation ensures that the constructs measure distinct aspects of investor behavior and technology adoption. These findings are consistent with Pinandhito et al. (2025), who reported that e-trust (trust in AI) can be empirically distinguished from financial literacy and technology adoption in the Indonesian retail investment context. This distinction is particularly important in emerging markets, where investors may adopt digital platforms without strong financial knowledge, or conversely, possess financial literacy but remain skeptical toward AI-based systems (Amalia & Subagyo, 2024). Hence, the HTMT analysis confirms that the constructs in this study are not only statistically valid but also theoretically and contextually relevant.

Table 7. R-Square.

	R^2	R-square adjusted
Investment Behavior	0.737	0.726
Portfolio Performance	0.656	0.637

Source: Results of data processing and using Smart PLS, 2025.

As presented in Table 7, the model demonstrates strong explanatory power. Investment Behavior achieved an R^2 value of 0.737, which is considered substantial (Hair et al., 2019). This implies that 73.7% of the variance in investment behavior is explained by robo-advisor usage, trust in AI, financial literacy, and risk tolerance. Similarly, Portfolio Performance obtained an R^2 value of 0.656, categorized as moderate, indicating that 65.6% of the variance in portfolio performance is accounted for by the antecedent variables, mediated through investment behavior. These findings underscore the pivotal role of investment behavior in translating cognitive, psychological, and technological factors into actual portfolio outcomes.

Table 8. Q2.

	SSO	SSE	Q^2 (=1-SSE/SSO)	Interpretation
Investment Behavior	800.000	473.831	0.408	High predictive relevance
Portfolio Performance	600.000	364.337	0.393	Medium predictive relevance

Source: Results of data processing and using Smart PLS, 2025

Table 8 reports the predictive relevance of the model using the Stone-Geisser Q^2 criterion. The construct Investment Behavior recorded a Q^2 value of 0.408, interpreted as high predictive relevance, while Portfolio Performance obtained a Q^2 value of 0.393, corresponding to medium predictive relevance. Both values exceed the recommended threshold of zero, confirming that the model has satisfactory predictive accuracy for out-of-sample data (Hair et al., 2019). These findings suggest that the integration of robo-advisor usage, trust in AI, financial literacy, and risk tolerance is not only theoretically robust but also empirically capable of predicting behavioral and performance outcomes. This result is consistent with previous studies that highlighted the predictive strength of behavioral finance models incorporating psychological and technological variables (Liu et al., 2023; Shahzad et al., 2024).

Table 9. f-square.

	f-square
Investment Behavior -> Portfolio Performance	0.155
Robo Advisor -> Investment Behavior	0.138
Robo Advisor -> Portfolio Performance	0.000
Trust In Ai -> Investment Behavior	0.001
Trust In Ai -> Portfolio Performance	0.206
Financial Literacy -> Investment Behavior	0.353
Financial Literacy -> Portfolio Performance	0.021
Risk Tolerance -> Investment Behavior	0.215
Risk Tolerance -> Portfolio Performance	0.000

Source: Results of data processing and using Smart PLS, 2025

Table 9 provides insights into the relative effect sizes of the predictor variables. Among the antecedents of investment behavior, Financial Literacy exerts the strongest influence ($f^2 = 0.353$, large effect), followed by Risk Tolerance ($f^2 = 0.215$, medium effect). These findings highlight that financial knowledge and attitudes toward risk are decisive factors shaping investment decisions. In contrast, the direct effect of Trust in AI on investment behavior is negligible ($f^2 = 0.001$), suggesting that trust, while important conceptually, does not directly translate into observable investment behaviors within this context.

Regarding portfolio performance, Trust in AI ($f^2 = 0.206$, medium effect) and Investment Behavior ($f^2 = 0.155$, medium effect) emerge as the most influential predictors. These results indicate that portfolio outcomes are primarily driven by rational investment practices and confidence in AI-based systems. By contrast, the direct effects of Robo Advisor usage and Risk Tolerance on portfolio performance are insignificant ($f^2 = 0.000$), implying that their contributions operate indirectly through investment behavior. These findings resonate with Pinandhito et al. (2025), who reported that behavioral and psychological mediators play a more decisive role than technological adoption alone in determining portfolio success.

Table 10. Path Coefficients.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Investment Behavior -> Portfolio Performance	0.451	0.417	0.136	3.302	0.001
Robo Advisor -> Investment Behavior	0.253	0.247	0.087	2.903	0.005
Robo Advisor -> Portfolio Performance	0.006	0.007	0.113	0.054	0.957
Trust in AI -> Investment Behavior	0.021	0.023	0.080	0.268	0.789
Trust in AI -> Portfolio Performance	0.364	0.380	0.112	3.263	0.002
Financial Literacy -> Investment Behavior	0.422	0.425	0.083	5.068	0.000
Financial Literacy -> Portfolio Performance	0.136	0.132	0.099	1.370	0.174
Risk Tolerance -> Investment Behavior	0.344	0.348	0.084	4.088	0.000
Risk Tolerance -> Portfolio Performance	-0.014	0.003	0.117	0.121	0.904

Source: Results of data processing and using Smart PLS, 2025

The results of the structural model estimation, focusing on the significance of the hypothesized paths. The values reported include the original sample coefficients (O), their standard deviations, t-statistics, and p-values. The results reveal varying levels of significance across the proposed relationships, offering empirical insights into the mechanisms through which technological, psychological, and cognitive factors shape investment behavior and portfolio performance. The findings demonstrate that Investment Behavior has a strong and statistically significant effect on Portfolio Performance ($\beta = 0.451$, $t = 3.302$, $p = 0.001$). This result highlights the pivotal role of behavioral practices in translating investor characteristics and technological adoption into tangible portfolio outcomes. Similarly, Robo Advisor significantly influences Investment Behavior ($\beta = 0.253$, $t = 2.903$, $p = 0.005$), suggesting that the adoption of robo-advisory services encourages investors to engage more actively and systematically in investment activities. However, the direct path from Robo Advisor to Portfolio Performance is not significant ($\beta = 0.006$, $t = 0.054$, $p = 0.957$), indicating that robo-advisory tools enhance performance indirectly, primarily through behavioral mediation rather than direct contribution. The role of Trust in AI reveals an interesting dynamic. Its direct impact on Investment Behavior is insignificant ($\beta = 0.021$, $t = 0.268$, $p = 0.789$), showing that trust alone does not drive investors to alter their behavior.

Trust in AI significantly contributes to Portfolio Performance ($\beta = 0.364$, $t = 3.263$, $p = 0.002$). This implies that while trust in AI may not immediately translate into observable behavioral changes, it enhances performance outcomes by fostering confidence in automated systems, potentially leading to more consistent and rational investment decisions. These findings resonate with prior studies emphasizing the indirect but crucial role of trust in shaping investor outcomes (Pinandhito et al., 2025; Xie et al., 2020). Financial Literacy emerges as a critical determinant of investment behavior. Its path to Investment Behavior is significant and strong ($\beta = 0.422$, $t = 5.068$, $p < 0.001$), confirming that financial knowledge equips investors with the ability to make informed and rational decisions. However, its direct path to Portfolio Performance is not statistically significant ($\beta = 0.136$, $t = 1.370$, $p = 0.174$), which suggests that literacy alone does not guarantee superior investment outcomes. Instead, its influence is primarily mediated through behavioral channels. This aligns with Lusardi and Mitchell (2023), who argue that financial literacy serves as a necessary but not sufficient condition for achieving positive portfolio outcomes. Similarly, Risk Tolerance has a significant positive impact on Investment Behavior ($\beta = 0.344$, $t = 4.088$, $p < 0.001$), indicating that individuals with higher tolerance for risk are more likely to engage actively in investment activities. Nevertheless, its direct effect on Portfolio Performance is insignificant ($\beta = -0.014$, $t = 0.121$, $p = 0.904$). This finding suggests that while risk tolerance shapes behavioral patterns, it does not directly translate into improved performance, possibly due to the moderating role of market conditions and the necessity of disciplined decision-making strategies.

Overall, the results in Table 10 reinforce the mediating role of Investment Behavior in linking antecedent variables robo-advisor usage, financial literacy, and risk tolerance to portfolio outcomes. While Trust in AI exerts a more direct influence on performance, the findings emphasize that behavioral factors remain the primary conduit through which knowledge, technological adoption, and attitudes toward risk impact investor success. This is consistent with the behavioral finance perspective, which underscores that cognitive, psychological, and technological variables interact to shape outcomes, rather than acting in isolation (Oehler et al., 2022; Lusardi & Mitchell, 2023).

5. Conclusions

The study shows that financial literacy and risk tolerance are the main factors shaping investment behavior, while robo-advisor use also plays an important role. Trust in AI may not directly change how people invest, but it does boost portfolio performance. Investment behavior acts as a key link between knowledge, risk attitudes, and technology adoption, underscoring that strong results come from a balance of financial skills, psychological traits, and consistent habits. These findings suggest that better financial education, disciplined investing, and fintech tools that build trust and support learning are essential for achieving long-term success.

Acknowledgments: The authors would like to dedicate this work to their beloved parents, whose endless prayers, love, encouragement, and trust have been the greatest source of strength throughout this academic journey. Gratitude is also extended to the Faculty of Economics and Business, Universitas Dian Nuswantoro, for the support and facilities provided during the research process. Special thanks go to Ms. Suhita Whini Setyahuni, SE, M.Ak, Ak, for her valuable guidance, encouragement, and insightful advice, as well as to all respondents who generously participated in this study. Finally, the authors sincerely acknowledge Mr. Haunan Damar, S.S.T, MBA, whose care, attention, and motivation as academic advisor since the third semester have continually inspired them to strive and grow.

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