Investor Trust in Robo-Advisors: The Impact of Perceived Risk, Control, and AI Predictive Capability

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ABSTRACT

This research investigates how perceived risks to data security and perceived control influence investors' trust in robo-advisors, as well as the impact of this trust on their adoption decisions. It also examined the moderating effect of the predictive advantage of machine learning. Employing a quantitative analysis method with Partial Least Squares Structural Equation Modeling (PLS-SEM), data were gathered from investors who are familiar with robo-advisors. The results indicate that perceived data security risk diminishes trust, whereas perceived control enhances trust. However, trust alone does not directly result in adoption, implying that other elements such as ease of use and economic benefits might be influential. The predictive advantage of machine learning enhances the link between trust and adoption but does not directly affect adoption decisions. Providers of robo-advisors should focus on improving algorithm transparency, bolstering data security systems, and offering features that enhance users' perceived control. Effective communication AI's predictive advantages of AI is also essential for building investor trust and alleviating security concerns. This study was constrained by its cross-sectional design, which limits the observation of long-term trust dynamics. Future studies should adopt a longitudinal approach and investigate additional factors such as regulatory influence and investor psychology. These findings contribute to the understanding of trust mechanisms in fintech adoption and offer strategic recommendations to industry professionals.

Keywords: *data security risk, trust level, perceived control of equity, investors' decision to adopt robot advisors***.**

1. INTRODUCTION

Financial markets are undergoing significant transformation, marked by the increasing integration of automation and algorithmic tools. This evolution has shifted the paradigm from traditional human-driven trading methodologies to strategies that are significantly enhanced by technology. A notable development in this landscape is the emergence of robo-advisors, initially conceived as platforms to democratize investment management for retail investors . These automated digital investment advisory programs gather information on users' financial goals, risk tolerance, and investment horizons to construct and manage investment portfolios. The core functionality involves algorithmic advice and automated execution, aiming to provide cost-effective and accessible investment solutions

Machine learning has been demonstrated to exhibit superior accuracy in stock market predictions compared with conventional statistical models (Bhattacharjee & Bhattacharja, 2019; Verma & Mohapatra, 2020; Agarwalla, 2024). This enhanced performance can be attributed to its capacity to discern non-linear relationships. These models can interpret complex patterns in data; however, they are susceptible to overlearning and do not ensure superior accuracy (Agarwalla, 2024; Grebovic et al., 2023).The implementation of supervised classification enhanced the prediction accuracy to 97%, surpassing the 82% accuracy achieved by linear regression (Verma & Mohapatra, 2020).

The objective of this study is to analyze the influence of perceived data security risk, trust level, and perceived control on equity investors' decision to adopt robo-advisors. Additionally, this study explores the extent to which the predictive capability of machine learning can increase investor trust by considering the risk of overlearning and algorithm transparency.

2. RESEARCH METHOD

This study employed quantitative methodologies utilizing an online questionnaire disseminated through SurveyMonkey to collect data. The research population comprised investors in the stock market, and the sample was selected through purposive sampling. The sample criteria encompassed active investors on the Indonesia Stock Exchange (IDX) who possessed knowledge of AI technology, particularly Robo-Advisor, as evidenced by their responses to a screening question. Table 1 presents the respondents' age demographics and their experiences in the stock market.

2.1. Population and samples

Table 1 provides a snapshot of trader demographics and experience levels. The majority of traders fall into the younger age group, with 36.84% being 20-24 years old (Generation Z) and a significant 56.58% combined in the 25-34 and 35-44 age ranges (Generation Y). This finding suggests a strong presence of younger generations in the trading space. In terms of experience, the data indicate that a substantial 64% identify as beginners, with a decreasing percentage as experience levels increase (28.95% intermediate, 3.95% advanced, and 2.63% expert). This distribution highlights a large number of novice traders in the observed group.

Table 1. Respondent Demographics

	Category	Generation	Percentage	Frequency
Age	20-24	Z	36.84	28
	25-34	Y	28.95	22
	35-44	Y	27.63	21
	45-55	X	6.58	5
Experience	Beginer		64	49
	Intermediate		28.95	22
	Advance		3.95	3
	Expert		2.63	2

2.2. Instrument validity and reliability

In the measurement instrument test stage, we eliminated PC3, PC4, PSDR1, PSDR2, RADP4, and RADP5 because their outer loading values fell below 0.7. The discriminant validity test indicated that all measurement criteria met the minimum threshold. VIF < 5 indicates that there is no multicorrelation among the items. The comprehensive results of the outer model tests are presented in Table 2.

Table 2. VIF and Outer Model Evaluation

Items	VIF	Outer Loading	Cronbach's Alpha	Rho_a	AVE
PC1	2.051	0.864	0.815	0.836	0.731
PC2	2.975	0.924			
PC5	1.772	0.769			
PSDR3	2.095	0.724	0.727	0.783	0.622
PSDR4	2.222	0.814			
PSDR5	1.174	0.825			
TR1	1.967	0.821	0.864	0.882	0.646
TR2	1.888	0.880			

Items	VIF	Outer Loading	Cronbach's Alpha	Rho_a	AVE
TR3	1.967	0.785			
TR4	2.831	0.751			
TR5	1.963	0.775			
PMLC 1	2.973	0.889	0.878	0.900	0.671
PMLC 2	1.899	0.786			
PMLC 3	2.444	0.837			
PMLC 4	2.440	0.817			
PMLC 5	2.096	0.763			
RADP1	2.040	0.895	0.818	0.846	0.731
RADP2	1.880	0.875			
RADP3	1.656	0.791			

Discriminant validity was assessed to ensure that each construct was distinct from the others. We used the Fornell-Larcker Criterion, which stipulates that the square root of the AVE for each construct should exceed its correlation with other constructs. We also employed Heterotrait-Monotrait Ratio (HTMT) analysis, with a recommended threshold of ≤ 0.85 (or ≤ 0.90 in less stringent cases). The results presented in Table 3 indicate that the Fornell-Larcker and HTMT ratios satisfied the model feasibility criteria.

Table 3. Fornell-Larcker and HTMT ratio

	PC	PMLC	PSDR	RADP	TR
PC	0.855	0.198	0.426	0.587	0.373
PMLC	0.253	0.819	0.108	0.336	0,499
PSDR	0.623	0.139	0.789	0.440	-0.205
RADP	0.767	0.376	0.658	0.855	0.174
TR	0.438	0.608	0.231	0.212	0.804

3. RESULT AND DISCUSSION

The utilization of PLS bootstrapping in hypothesis testing has yielded noteworthy insights concerning the adoption of robo-advisors by equity investors. The following hypothesis was proposed:

H1: Perceived data security risk affects equity investors' trust in robo-advisors.

H2: Perceived control affects equity investors' trust in robo-advisors.

H3: Investors' trust in robo-advisors influences investors' decision to adopt robo-advisors.

H4: Predictive machine learning capability moderate the nexus between investors' trust in robo-advisors on investors' decision to adopt robo-advisors.

The fourth hypothesis posits that the predictive advantage of machine learning in robo-advisory services moderates the relationship between investors' trust in robo-advisors and their decision to adopt robo-advisors.

Table 4. Path Coefficient and P Value

	Original Sample	Sample Mean	STDEV	P Values
PC → TR	0.588	0.539	0.167	0.000
PMLC → RADP	0.213	0.262	0.178	0.230
PMLC x TR → RADP	0.355	0.293	0.147	0.016
PSDR → TR	-0.474	-0.365	0.225	0.035
TR → RADP	0.122	0.116	0.219	0.578

3.1. The Effect of Perceived Data Security Risk on Trust in Robo-Advisors (H1)

The analysis shows that Perceived Data Security Risk (PSDR) negatively affects trust in robo-advisors (TR), with a path coefficient of -0.474 and a p-value of 0.035. This indicates that the higher the data security risk perceived by investors, the lower their trust in robo-advisors significantly.

This result aligns with the Perceived Risk Theory proposed by Bauer (1960), which posits that individuals tend to avoid options perceived to carry high risk in decision-making, a tendency that extends to the use of financial technology, such as robo-advisors. This finding is further substantiated by prior research: Specifically, Roh et al. (2023) and Singh (2024) found that perceptions of data security and privacy significantly influence users' trust in robo-advisory platforms, while Wu & Gao (2021) demonstrated that perceived risk can reduce adoption intention towards AI-based financial technology. Moreover, research by Kim et al. (2008) in the context of e-commerce and fintech also demonstrated that the higher the perceived data security risk, the lower the level of user trust in digital services. These findings are consistent with previous literature and confirm that investors' trust in robo-advisors is highly dependent on their perception of data security.

3.2. The Effect of Perceived Control on Trust in Robo-Advisors (H2)

The present study examined the influence of perceived control (PC) on trust in robo-advisors (TR). The findings revealed a positive and significant relationship, with a path coefficient of 0.588 and p-value of 0.000. These results suggest that investors who perceive greater control over the robo-advisory process tend to place greater trust in the platform.

This finding aligns with the Perceived Control Theory proposed by Skinner (1996), which posits that individuals tend to trust and feel more comfortable with a system or technology if they perceive that they have control over the process and decisions taken. In the context of robo-advisory, this heightened sense of control leads to a corresponding increase in investor trust in the platform.

This finding aligns with prior research indicating that, in the context of digital banking services, perceived control fosters heightened user trust because of its capacity to mitigate uncertainty and enhance a sense of security (Yousafzai et al., 2004). Studies examining automation and human-machine interaction have demonstrated that users' trust in technology-based systems is augmented when they perceive having control over the process (Mital & Ghahramani, 1994). Furthermore, within the domain of digital financial services, studies have shown that users who perceive a high degree of autonomy in their investment decision-making are more likely to place trust in automated platforms such as robo-advisors (Rita et al., 2019).

3.3. The Effect of Trust in Robo-Advisors on Adoption Decisions (H3).

The findings indicate that trust in robo-advisors (TR) does not exert a substantial influence on investors' decision to adopt robo-advisors (RADP), with a path coefficient of 0.122 and a p-value of 0.578. This finding suggests that, while trust is a significant factor, it may not be the sole determining element in the adoption decision. This outcome is inconsistent with the majority of the literature on technology adoption, which emphasizes the pivotal role of trust. However, this discrepancy can be rationalized through the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), which posits that technology adoption is influenced by multiple key factors, including performance expectations, effort expectations, social influence, and facilitating conditions, rather than solely determined by trust.

This finding is corroborated by a study conducted by Ghazizadeh et al. (2011), who demonstrated that, in the context of automation systems, trust alone is insufficient to ensure technology adoption. Instead, factors such as perceived usefulness and ease of use emerged as more significant determinates of adoption decisions. The findings of this study substantiate that trust in robo-advisors is not the sole factor influencing adoption. Consequently, factors such as ease of use, economic benefits, and external influences may exert a more substantial influence on investors' decisions.

3.4. Moderating Role of Predictive Capability of Machine Learning in the Relationship between Trust and Adoption Decision (H4)

Predictive superiority of machine learning (PMLC) significantly moderates the relationship between trust in robo-advisors (TR) and adoption decision (Robo-Advisor Adoption - RADP), with a path coefficient of 0.355 and a p-value of 0.016. This finding suggests that when the predictive advantage of machine learning is considered high, the influence of trust on adoption decisions becomes stronger. The present findings are corroborated by the results of previous studies. For example, a 2024 study by Żywiołek on artificial intelligence (AI) and trust found that perceived intelligence of AI increases trust and strengthens the adoption intention of AI-based technologies in financial decision-making.

The outcomes can be elucidated through the Technology-Organization-Environment (TOE) Framework (Tornatzky & Fleischer, 1990) and the Trust-Technology Fit Theory (Lankton et al., 2015). The Technology-Organization-Environment (TOE) Framework posits that technology adoption is influenced by technological, organizational, and environmental factors. In this context, the predictive advantage of machine learning (technology aspect) strengthens the impact of trust (organization/individual aspect) on adoption decisions. When investors have confidence in AI's ability to make accurate predictions, they are more likely to adopt robo-advisors, as their trust in the technology increases. According to the Trust-Technology Fit Theory, for technology to be widely adopted, it must fit the needs of users and be trusted. The enhanced predictive capabilities of machine learning further reinforce the perception that robo-advisors can offer more precise recommendations, thereby amplifying the influence of investor trust on adoption decisions.

The findings indicate that, while trust is a critical component in the adoption of robo-advisors, the predictive capabilities of machine learning serve to amplify its impact. Consequently, developers of robo-advisory systems are required to enhance transparency and communication regarding the accuracy of AI-based predictions, with the objective of fostering investor trust and facilitating the adoption of these systems.

3.5. The Direct Effect of Predictive Superiority of Machine Learning on Adoption Decision.

The direct relationship between Predictive Superiority of Machine Learning (PMLC) and adoption decision (Robo-Advisor Adoption—RADP) is not statistically significant, with a path coefficient of 0.213 and a p-value of 0.230. This finding suggests that while the predictive ability of machine learning may shape investor perceptions, it does not directly influence adoption decisions.

This finding can be explained through the Technology Acceptance Model (TAM) (Davis, 1989) and the concept of perceived usefulness vs. perceived trust in financial technology adoption (Gefen et al., 2003). The Technology Acceptance Model (TAM) posits that while perceived usefulness is a significant factor in technology adoption, it must be balanced with perceived ease of use and trust to result in an adoption decision.In this context, although the predictive advantage of machine learning increases the usability of the system, other factors such as perceived risk, regulation, and user experience also play an important role.

Gefen et al. (2003) found that, in the adoption of internet-based services, trust plays a more significant role in users' decisions than mere technology usability. In other words, although investors are aware of the predictive advantages of robo-advisors, they still consider the risk and trust aspects before adopting them.

Akhtar et al. (2024) in a study on AI in financial services found that, despite the superior predictive capabilities of AI, its adoption was not automatically increased, as investors continued to rely on subjective factors such as trust and prior experience in making decisions.

4. CONCLUSION

The present study demonstrates that investors' perception of data security risk negatively impacts their trust in robo-advisors, while their perception of control has a significant positive influence. However, trust in robo-advisors does not directly influence adoption decisions, suggesting that other factors, such as ease of use and economic benefits, also play a role in investors' decisions. The predictive advantage of machine learning functions as a moderator, thereby reinforcing the relationship between trust and adoption decisions. However, it exerts no direct influence on the adoption of robo-advisors.These findings underscore the significance of algorithm transparency and the enhancement of communication regarding AI predictive accuracy. Such measures are instrumental in fostering investor trust and propelling the adoption of robo-advisory systems.

In order to promote the widespread utilization of robo-advisors, it is imperative that developers and service providers place significant emphasis on ensuring algorithm transparency, fortifying data security systems, and incorporating features that enhance users' sense of autonomy. Moreover, the lucid communication of AI's predictive advantages is crucial for fostering investor confidence, while concurrently addressing concerns pertaining to security risks and algorithm transparency.

This study is subject to several limitations that should be considered in future research. First, the study focuses on the trust factor and the adoption of robo-advisors without considering other variables, such as regulation, investor psychological factors, and financial market conditions that may affect investment decisions. Second, the study uses cross-sectional data, so it cannot capture changes in investor perceptions in the long term. To enhance the comprehensiveness of future studies, it is recommended that researchers employ a longitudinal approach to investigate the evolution of trust and the adoption of robo-advisors over time.

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Apendix A. Screening Question

How familiar are you with robo-advisor?

What factors do you consider most important when choosing an investment advisor?
How concerned are you about data security when using robo-advisors?
How fair and impartial do you believe AI systems are in making investment decisions?
How important is human interaction to you when receiving financial advice?
How much do you trust AI systems to provide reliable investment recommendations?
How much experience do you have using AI systems for investment decisions?

Perceived Data Security Risk

I am concerned that my personal and financial data may be accessed by unauthorized parties when using AI-based investment systems. (PSDR1)
I worry about potential cyberattacks or data breaches when using AI-driven financial services. (PSDR2)
I feel that AI investment platforms do not provide sufficient guarantees for the security of my personal data. (PSDR3)
I am skeptical about how well AI systems protect sensitive investment information. (PSDR4)
I believe that AI-based financial systems are vulnerable to data leaks. (PSDR5)

Perceived Control

I feel that I can control how AI systems use my personal data. (PC1)
I have the ability to adjust AI settings to align with my preferences and needs. (PC2)
I feel confident in my ability to manage potential risks associated with AI usage. (PC3)
I can decide when and how to interact with AI without feeling forced or dependent on it. (PC4)
I believe I have enough knowledge and resources to use AI responsibly and safely. (PC5)

Trust in AI

I trust AI-based investment systems to provide reliable recommendations. (TR1)
I believe AI-driven financial advice is as credible as advice from human experts. (TR2)
I am confident in the ability of AI investment platforms to make sound financial decisions. (TR3)
I rely on AI recommendations when making investment decisions. (TR4)
I feel comfortable following AI-generated investment advice. (TR5)

Predictive AI Capability

The AI system can accurately predict future trends based on past data. (PMLC1)
The AI system provides reliable recommendations that align with real-world outcomes. (PMLC2)
I believe the AI system can effectively anticipate my needs and preferences. (PMLC3)
The AI system continuously improves its predictions over time through learning from new data. (PMLC4)
I trust the AI system to make accurate forecasts in complex and uncertain situations. (PMLC5)

Willing to adopt robo-advisor
I am willing to use a robo-advisor for financial decision-making in the future. (RADP1)
I would consider relying on a robo-advisor to manage my investments. (RADP2)
I am open to replacing traditional financial advisors with a robo-advisor for certain financial tasks.(RADP3)
I feel comfortable using a robo-advisor to provide personalized financial recommendations.(RADP4)
I am likely to adopt a robo-advisor if it offers better convenience and lower costs than human advisors. (RADP5)