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INVESTOR BEHAVIOR MODEL TOWARD TRADING ROBOTS: AN INITIAL TRUST AND SOCIAL INFLUENCE APPROACH

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Abstract

This study aims to analyze investor behavior in adopting trading robots by highlighting the role of initial trust and social influence on behavioral intentions. The urgency of this research lies in the rapid growth of robo-advisor services in Indonesia, which still faces challenges such as low financial literacy and weak initial investor trust, while investment decisions are often influenced by social opinions. The study population includes individuals aged 17–59 years who use trading robots, with a total of 167 respondents obtained through an online questionnaire. Data analysis was conducted using a quantitative method with Structural Equation Modeling–Partial Least Squares (SEM–PLS). The results indicate that social influence has a significant effect on both initial trust and behavioral intention. In addition, initial trust positively influences behavioral intention and serves as a mediator in the relationship between social influence and behavioral intention. Meanwhile, the age variable does not moderate the relationship between initial trust and behavioral intention. These findings emphasize that initial trust is a key factor in shaping investors' intentions to adopt trading robots. Therefore, service development strategies should focus on strengthening trust from the early stages of user interaction and enhancing social influence through education, testimonials, and community engagement.

Keywords: Social Influence, Behavioral Intention, Initial Trust, Age, Financial behavior.

INTRODUCTION

The development of technology in the financial sector has driven the emergence of various artificial intelligence–based services, one of which is trading robots or robo-advisors. This technology has transformed the way investors, particularly retail investors, manage their finances. Through automated systems with minimal human intervention, robo-advisors are capable of providing investment recommendations and managing portfolios independently (Zhu et al., 2024). Advantages such as efficiency, data-driven personalization, and easy accessibility have made this technology increasingly attractive (Belanche et al., 2019). However, despite its growing global adoption, robo-advisors still face several challenges, particularly related to low initial trust from investors and uneven levels of financial literacy (Fecht et al., 2018). Moreover, social influence factors such as user testimonials or endorsements from public figures have also been found to affect individuals' decisions to use this technology. Therefore, to understand the adoption pattern more comprehensively, it is necessary to explore how initial trust and social influence shape investor behavior toward the use of robo-advisors.

The phenomenon of robo-advisor growth is also evident in Indonesia. Since 2021, the use of robo-advisors has shown a significant upward trend, marked by the introduction of the first licensed robo-advisor service by the Bareksa platform, officially authorized by the Financial Services Authority (OJK) (Alam & Achjari, 2024). By 2023, this technology has been implemented in several popular investment applications such as Bibit, Stockbit, Bambu, Halofina, and Reliance. This growth is mainly driven by the younger generation,

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who are more familiar with digital technology. According to Statista (2023), the number of robo-advisor users in Indonesia is projected to reach 11.2 million by 2027, exceeding the figures in Malaysia and Singapore. This rapid increase is driven by factors such as accessibility, low transaction fees, and user-friendly registration processes. Nevertheless, challenges remain, particularly regarding the low level of financial literacy among the public. Many novice investors tend to make decisions based on social trends or others' opinions rather than understanding their risk profiles and basic investment principles. This condition highlights the importance of further research on Indonesian investors' behavior toward robo-advisors, focusing on the role of initial trust and social influence as key determinants.

Initial trust emerges as one of the most critical challenges in the adoption of robo-advisors in Indonesia. As a relatively new technology, many users lack prior experience, leading to skepticism during early interactions. In the context of digital banking, Setiyono et al. (2022) found that information quality, service provider reputation, and customer support significantly influence users' initial trust levels. This aligns with Kern and Dethier (2022), who revealed that transparent, customizable robo-advisor systems that still allow for some degree of human control are more easily trusted by new users. In a volatile market environment, initial trust becomes an essential factor determining whether individuals are willing to entrust their financial decisions to AI-based automated systems. Without adequate trust, the adoption of such technology will face serious barriers.

Equally important, social influence has been proven to play a significant role in shaping decisions to adopt robo-advisor technology. This influence encompasses how opinions from friends, family, or public figures shape individual perceptions and interests toward the service. A study by Zhafira et al. (2025) using the UTAUT2 model found that social influence is one of the most significant variables driving user interest in technology-based financial services. Social support not only arises from direct interactions but also from social media, online testimonials, and influencer marketing campaigns (Hasanah, 2024). In today's digital era, this form of influence is particularly effective among younger generations, who are more responsive to collective opinions. Therefore, educational and public communication strategies that consider social aspects are crucial to encourage higher adoption rates.

Behavioral intention serves as a reflection of the degree to which investors are inclined to use trading robot services. Based on a study by Gan et al. (2021), five main factors significantly influence consumers' behavioral intentions toward robo-advisor use: performance expectancy, social influence, trust, perceived financial knowledge, and reliance tendency on robo-advisors. Individuals who believe that the technology can enhance financial management effectiveness and feel comfortable relying on it tend to have stronger adoption intentions. Trust in a system perceived as secure and unbiased, combined with individuals' confidence in their financial understanding, further reinforces their decision. In Indonesia—where literacy and trust remain challenges—understanding behavioral intention is crucial for designing more inclusive, targeted, and sustainable technology adoption strategies.

Beyond psychological and social factors, demographic characteristics such as age also differentiate technology adoption patterns among investors. Gan et al. (2021) reported that age correlates with levels of trust and preference toward robo-advisor usage, with younger groups showing a higher adoption intention than older ones. This is consistent with a survey by Investopedia (2023), which revealed that most robo-advisor users are aged between 20 and 40 years, while participation among users aged 50 and above remains relatively low. This difference is attributed to younger generations' higher comfort with digital technology and their openness to innovation in investment management. Furthermore, Investopedia (2022) reported that affluent millennials demonstrate growing preferences for robo-advisors due to their efficiency, automation, and service personalization. Hence, age not only functions as a demographic variable but also reflects differences in digital literacy, risk perception, and financial decision-making patterns—all of which contribute to varying adoption behaviors across age groups. Therefore, when constructing an investor behavior model toward trading robots, it is essential to consider age as a moderating variable influencing the relationship between initial trust, social influence, and behavioral intention.

Although previous studies on investor behavior toward robo-advisors have developed considerably, research gaps still exist. For instance, Iqbal and Aamir (2025) in Pakistan proposed a UTAUT-based model focusing primarily on trust propensity and technological conditions influencing initial trust, placing age as a moderator between trust propensity and initial trust. However, their model did not integrate the mediating role of initial trust in the relationship between social influence and behavioral intention. In contrast, the model proposed in this study offers a more comprehensive approach by testing both direct and indirect relationships among social influence, initial trust, and behavioral intention, while also introducing age as a moderating variable. Thus, this study not only broadens the understanding of psychological and social factors influencing the adoption of trading robots but also contributes theoretically by examining a more complex and contextual structural model tailored to Indonesia's unique market characteristics.

LITERATURE REVIEW

Behavioral Intention to Use Trading Robots

Behavioral intention serves as a primary indicator of an individual's readiness to adopt a particular technology in the near future. In the context of financial robo-advisors, this intention is essential for understanding technology adoption among young investors. Nourallah (2023) emphasizes that behavioral intention toward financial robo-advisors is directly influenced by users' initial trust in the system. Similarly, Gu (2015) states that users who feel comfortable, confident, and perceive benefits from digital technology show a greater tendency to use it continuously. This finding aligns with Beketov (2018), who highlights that transparency and reliability in robo-advisor systems strengthen young investors' behavioral intention to engage in digital investment activities. Hence, behavioral intention reflects not only user motivation but also the outcome of trust, perceived usefulness, and the credibility of technology-driven financial services.

Initial Trust

Initial trust refers to a preliminary level of confidence formed before an individual gains direct experience with a system. It plays a vital role in fostering acceptance of new technology. Rousseau (1998) defines initial trust as a psychological condition representing a willingness to accept risk based on positive expectations of another party. In the digital context, Gu et al. (2016) found that privacy concerns, trust propensity, performance expectancy, facilitating conditions, and hedonic motivation significantly influence the formation of initial trust. Additionally, Beketov (2018) asserts that transparency and reliability in robo-advisor systems enhance users' early perceptions, fostering confidence in digital services even without direct experience. Collectively, these studies demonstrate that initial trust is the foundational element in the early adoption of technology-based services.

Social Influence

Social influence represents the extent to which individuals are affected by the opinions of others when making decisions, including in the use of financial technology. In the context of financial robo-advisors, Nourallah (2023) found that social influence plays a significant role in shaping initial trust among young investors in Malaysia, highlighting the importance of opinions from close social circles in building early trust in AI-driven systems. However, this effect was not found to be significant in Sweden, suggesting that the strength of social influence varies across collectivist and individualist cultures. On a broader scale, Cho (2016) explains that social norms emphasizing fairness, such as gender equality, can increase the level of social trust within a society. This indicates that a supportive and equitable social environment strengthens trust and encourages individuals to engage in behaviors considered common or socially endorsed.

Age

Age functions not only as a direct demographic factor influencing attitudes toward technology adoption but also as a moderating variable that can strengthen or weaken the relationship between technology perception and behavioral intention. In the context of AI-based financial services such as robo-advisors, age influences the extent to which initial trust and perceived usefulness drive adoption behavior. Shum (2024) found that higher age correlates with lower digital literacy, greater insecurity about technology, and limited access to digital tools, which in turn reduce the positive effects of optimism and trust toward technology. This means that even when two individuals share the same level of initial trust, their behavioral intentions may differ depending on age. Conversely, Moon (2025) found that age moderates information acceptance from AI systems, where younger individuals display greater openness to AI-generated recommendations than older groups. These findings collectively suggest that age serves as a moderating factor between cognitive elements (such as initial trust and information perception) and technology adoption behavior, including the use of digital financial services like robo-advisors.

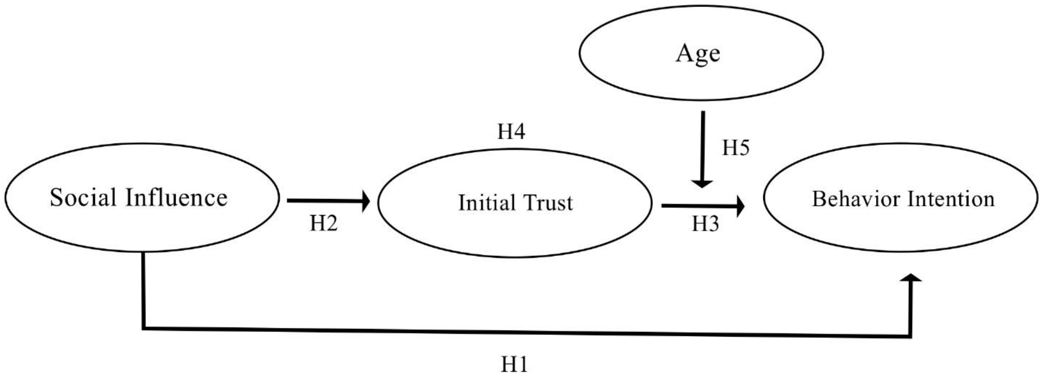

Figure 1. Conceptual Framework

Hypotheses of the Study:
H1: Social influence has a significant effect on behavioral intention.
H2: Social influence has a significant effect on initial trust.
H3: Initial trust has a significant effect on behavioral intention.
H4: Initial trust mediates the effect of social influence on behavioral intention.
H5: Age moderates the effect of initial trust on behavioral intention.

METHOD

This study employs a quantitative approach with a population consisting of all individuals in Indonesia who use trading robots as tools in their investment activities. The defined population characteristics include all genders within the age range of 17 to 59 years, representing the productive age group. The sample size in this study was determined based on the recommendation of Hair et al. (2010), who stated that an appropriate sample size for Structural Equation Modeling (SEM) ranges between 100 and 200 respondents to produce stable and reliable estimations. The research sample was obtained through the distribution of online questionnaires to respondents who met the specified criteria. The collected data were then processed and analyzed using the Structural Equation Modeling–Partial Least Squares (SEM–PLS) method, with the expectation that the results would provide a deeper understanding of investor behavior toward the use of trading robots.

RESULTS AND DISCUSSION

Descriptive Analysis of Respondents

After distributing the questionnaire, this study successfully collected data from 167 respondents. This number is considered sufficiently representative of the target population. To provide a clearer picture of the participant profile, respondent characteristics, such as gender, age, education level, and experience using trading robots, are summarized and presented in Table 1.

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Table 1. Respondent Characteristics

Characteristics	Total	Percentage
Gender		
Man	46	27,54%
Woman	121	72.46%
Amount	167	100%
Latest Education		
High School (SMA)	62	37,1%
Diploma (D1–D3)	11	6,6%
Bachelor's Degree (S1)	72	43,1%
Master's/Doctoral Degree (S2/S3)	22	13,2%
Amount	167	100%
Age		
Under 20	18	10,78%
20-29	131	78,44%
30–39	12	7,19%
40-49	4	2,40%
Over 50	2	1.20%
Total	167	100%

Based on Table 1, it can be seen that the respondents in this study numbered 167 people. In terms of gender, respondents were dominated by women at 121 people (72.46%), while men numbered 46 people (27.54%), indicating that women's participation in the use of digital financial services is relatively higher. Viewed from the last level of education, the majority of respondents were Bachelor's graduates (S1) as many as 72 people (43.1%), followed by high school/vocational high school graduates or equivalent as many as 62 people (37.1%), postgraduate (S2/S3) as many as 22 people (13.2%), and Diploma (D1–D3) as many as 11 people (6.6%). Meanwhile, if seen from the age aspect, most of the respondents are in the 20-29 years age group, namely 131 people (78.44%), then less than 20 years old as many as 18 people (10.78%), aged 30-39 years as many as 12 people (7.19%), aged 40-49 years as many as 4 people (2.40%), and more than 50 years as many as 2 people (1.20%). This distribution shows that the majority of respondents come from the young productive age group with a relatively high level of education, as well as the participation of women is more dominant, so it can illustrate that the younger generation, especially women with a bachelor's degree, is a potential market segment in the use of digital-based financial technology.

Table 2. Respondent's Answer Interval Length

Interval	Category
1,00-1,80	Strongly Disagree
1.81-2,60	Disagree
2,61-3,40	Somewhat Agree

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Interval	Category
3,41-4,20	Agree
4,21-5,00	Strongly Agree

The data obtained from the results of distributing the questionnaires were processed to determine the descriptive statistical test consisting of mean analysis and value variation analysis which function to determine the distribution of variable values such as standard deviations, the descriptive statistical test in this study is as follows:

Table 3. Descriptive Statistics

Variabel	Items	Mean	Std. Devition
Behaviour Intention	BI01	3,99	0,76
	BI02	3,86	0,85
	BI03	3,93	0,80
	BI04	3,70	0,91
	BI05	3,77	0,87
	BI06	3,68	0,90
Intial Trust	IT01	4.03	0,76
	IT02	4,04	0,76
	IT03	4,01	0,78
	IT04	3,89	0,83
	IT05	3,69	0,92
	IT06	3,87	0,80
Social Influence	SI01	3,51	0,92
	SI02	3,56	0,97
	SI03	3,56	0,93
	SI04	3,76	0,97
	SI05	3,81	0,95
	SI06	3,79	0,90

Based on the descriptive analysis of the Behavioral Intention variable, the indicator with the highest mean score was BI01, with a score of 3.99, falling within the 3.41–4.20 range, categorized as "Agree." This indicates that the average respondent agreed with the statement in this indicator. Meanwhile, the indicator with the lowest mean score was BI06, with a score of 3.68, also falling within the "Agree" category, but with a lower level of agreement than the other indicators. In terms of response diversity, the highest standard deviation value was found in BI04 (0.91), indicating significant variation in responses. The lowest standard deviation was found in BI01 (0.76), indicating a more homogeneous response.

Furthermore, for the Initial Trust variable, the indicator with the highest mean score was IT02, with a score of 4.04, falling within the 4.21–5.00 range, categorized as "Strongly Agree." This indicates that the average respondent strongly agreed with the statement in this indicator. The indicator with the lowest mean was IT05, with a value of 3.69, which falls into the "Agree" category. Respondents tended to agree, but at a lower level than other indicators in this variable. In terms of data distribution, the highest std. deviation value was found in IT05 (0.92), indicating a fairly high diversity of responses. While the lowest std. deviations were found in IT01 and IT02 (0.76), indicating relatively consistent responses.

For the Social Influence variable, the indicator with the highest mean value was SI05, with a value of 3.81, falling within the 3.41–4.20 range, categorized as "Agree." This indicates that respondents agreed with the statement in this indicator. Conversely, the indicator with the lowest mean was SI01, with a value of 3.51, which also falls into the "Agree" category, but at the lowest level of agreement compared to other indicators. In terms of data distribution, the highest std. deviations were found in SI02 and SI04 (0.97), indicating greater variation in respondents' responses. The lowest deviation was in SI06 (0.90) which indicates that respondents' answers were more homogeneous.

Outer Model Results

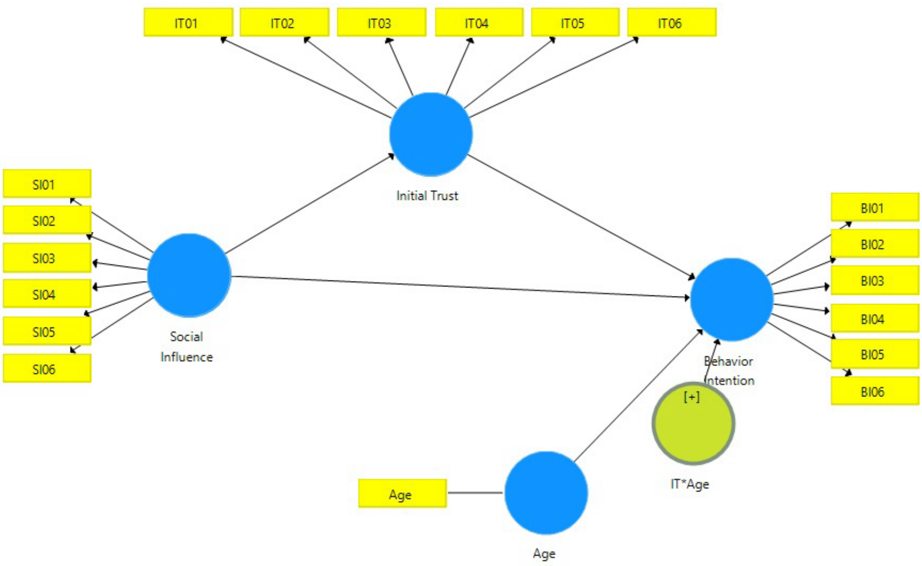

Figure 2. Outer Model

Convergent Validity

A good correlation level in convergent validity can be seen from the average variance inflation factor (AVE) value, which must be greater than or equal to 0.7. Ghozali & Latan, (2015)

Table 4. Outer Loading and Average Variance Extracted

Variabel	Item	Outer Loading	AVE
Behaviour Intention	BI01	0,821	0,688
	BI02	0,891	
	BI03	0,849	
	BI04	0,808	

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	BI05	0,822	
	BI06	0,781	
Initial Trust	IT01	0,885	0,719
	IT02	0,837	
	IT03	0,846	
	IT04	0,845	
	IT05	0,851	
	IT06	0,823	
Social Influence	SI01	0,811	0,710
	SI02	0,891	
	SI03	0,871	
	SI04	0,852	
	SI05	0,815	
	SI06	0,810	

Based on table 4, it can be concluded that the indicators in each construct have a good correlation and are declared valid, because they have met the criteria of an average variance extracted (AVE) value greater than 0.5 and a loading factor exceeding 0.7.

Reliability Test

Reliability tests are conducted to ensure that the indicators used can provide consistent and accurate results in measuring a construct. Reliability can be tested using Cronbach's Alpha, with a minimum value of 0.6, and Composite Reliability, with a minimum value of 0.7. Thus, the test results can be declared reliable and accurate.

Table 5. Cronbach’s Alpha dan Composite Realiability

Indikator	Cronbach's Alpha	Composite Reliability
Age	1,000	1,000
Behaviour Intention	0,909	0,929
Initial Trust	0,922	0,939
Social Influence	0,918	0,936

Based on Table 5, it is known that the indicator is able to test the construct precisely and accurately because it has met the criteria of a minimum Cronbach's Alpha value of 0.7 and a minimum Composite Reliability value of 0.7.

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Coefficient of Determination

The coefficient of determination, or R^2 value, indicates the extent to which the variation of a variable can be explained by other variables used in the study and external variables. The ideal R^2 value is between 0 and 1 (Hamid & Anwar, 2019).

Table 6. R^2

Variabel	R^2
Behavior Intention	0,702
Initial Trust	0,454

The R^2 value for the Initial Trust variable of 0.454 can be interpreted as indicating that the construct used in this study can explain 45.4% of the variability in Initial Trust, while the remaining 54.6% is explained by other constructs outside the study. Meanwhile, the R^2 value for the Behavior Intention variable of 0.702 indicates that the variables used in the research model can explain 70.2% of the variability in Behavior Intention, with the remaining 29.8% influenced by other factors outside the study. Thus, the R^2 values for both variables are in the moderate to strong category, indicating that this research model has quite good explanatory power for the dependent variable studied.

Model Testing

Model testing in this study was conducted using the predictive relevance method using the Q^2 value (Haryono, 2016). If the Q^2 value is > 0, the model is considered to have good predictive relevance. Conversely, if the Q^2 value is < 0, this indicates that the model has no predictive relevance or poor relevance (Hair et al., 2019).

Table 7. Q^2

Variabel	Q^2
Behavior Intention	0,473
Initial Trust	0,314

Based on Table 7, it is known that the Q^2 value of the Behavior Intention Variable is 0.229 and the Q^2 value of purchase intention is 0.492 so it is more than 0 which means that the variable model has good predictive relevance.

Hypothesis Testing

Table 8. Hypothesis Testing

Hypothesis	P Value	Description
H1: Social Influence -> Behaviour Intention	0,004	Accepted
H2: Social Influence -> Initial Trust	0,000	Accepted
H3: Initial Trust -> Behaviour Intention	0,000	Accepted
H4: Social Influence -> Initial Trust -> Behavior Intention	0,000	Accepted
H5: Initial Trust*Age -> Behaviour Intention	0,373	Rejected

The results of the hypothesis testing showed several important findings. Social Influence was proven to have a significant effect on Behavioral Intention ($p = 0.004 < 0.05$), so H1 was accepted, which means that social encouragement from the environment plays a role in shaping investors' intentions to adopt technology. Not only that, Social Influence also had a significant effect on Initial Trust ($p = 0.000 < 0.05$), so H2 was accepted, indicating that the stronger the social influence a person receives, the higher the level of initial trust formed. Furthermore, H3 was also accepted with the same small p-value ($p = 0.000 < 0.05$), confirming that Initial Trust is a key factor in shaping Behavioral Intention. In H4, it was found that Age had a significant effect on Behavioral Intention ($p = 0.000 < 0.05$), indicating differences in the tendency of adoption intentions between age groups. However, different results emerged in H5 which tested the moderating role of Age in the relationship between Initial Trust and Behavioral Intention. With a p-value of 0.373 (>0.05), H5 is rejected, which means that age differences are not able to strengthen or weaken the influence of initial trust on behavioral intentions, so it can be concluded that the influence of initial trust on usage intentions is relatively consistent across age groups.

The Effect of Social Influence on Behavioral Intention

The analysis results show that social influence has a significant effect on behavioral intention ($p = 0.004 < 0.05$), thus H1 is accepted. This finding confirms that the stronger the social pressure an individual receives from their environment, the greater their tendency to use robot trading services. This means that investors' decisions to adopt digital financial technology are not only influenced by internal factors but also by the opinions, recommendations, and experiences of those around them. These results are consistent with research by Jaya et al. (2021), who found that social influence increases the behavioral intention of Traveloka users, and Dewi and Lestari (2024), who demonstrated that social influence influences the intention to use GrabFood both directly and in combination with other factors. In the context of robo-advisors, Gan et al. (2021) also emphasized the important role of social influence, particularly during the COVID-19 pandemic when the need for technology-based investment solutions increased. Therefore, it is understandable that social influence is a consistent factor that strengthens investors' confidence in adopting robot trading.

The Influence of Social Influence on Initial Trust

Analysis of H2 shows that Social Influence also significantly impacts Initial Trust ($p = 0.000 < 0.05$). These results indicate that social support from the surrounding environment, whether through recommendations from family, friends, or the community, can build initial trust in trading robot services, even before investors have direct experience using them. This finding aligns with Nourallah (2023), who emphasized the role of social influence in reducing uncertainty in the early stages of adoption, and Alkhalifah (2022), who highlighted the role of social influence as external validation of the reliability of new technology. Araluze and Plaza (2023), in the context of open banking, also emphasized the direct contribution of social influence to the formation of initial trust. In other words, social support can be viewed as a gateway that provides a sense of security for investors who are still hesitant. Thus, the initial trust formed through social interactions serves as a crucial foundation before they are truly convinced to adopt trading robots.

The Influence of Initial Trust on Behavioral Intention

The results of the H3 test indicate that Initial Trust significantly influences Behavioral Intention ($p = 0.000 < 0.05$). This means that the higher the level of initial trust investors have in robot trading services, the greater their intention to use them. Initial trust plays a crucial role in reducing uncertainty, allowing investors to feel more confident in adopting them even without direct experience. These results align with Saintz (2021), who found that initial trust drives interest in using the digital payment application OVO, and Gallardo et al. (2024), who emphasized the crucial role of trust in the intention to use telemedicine among elderly Filipinos. In the context of robo-advisors, Nourallah et al. (2023) also emphasized that initial trust influences user acceptance because it provides basic confidence in the system's reliability. Thus, initial trust can be viewed as a fundamental factor that not only reduces doubt but also acts as a psychological driver for investors to adopt AI-based technologies.

The Role of Initial Trust in Mediating Social Influence on Behavioral Intention

In H4, the results showed that Initial Trust mediates the relationship between Social Influence and Behavioral Intention. This means that social influence from the environment does not directly drive usage intention, but first strengthens initial trust, which then becomes an important foundation for forming behavioral intention. This finding aligns with Karunasingha and Abeysekera (2022), who found that trust acts as a mediator between social motivation and purchase intention in digital marketing, and Fischer et al. (2023), who demonstrated a similar pattern in human-robot interactions, where trust mediates first impressions on usage intention. Singh and Kumar (2025), in the context of robo-advisors, also found that although social influence does not directly influence user attitudes, trust plays a significant role in shaping attitudes and intentions. Therefore, this study confirms that social encouragement is only truly effective if it successfully builds initial trust. Therefore, trading robot adoption strategies need to emphasize efforts to foster trust from the early stages of user interaction.

The Role of Age in Moderating Initial Trust on Behavioral Intention

H5 testing showed that age did not play a significant role as a moderator in the relationship between Initial Trust and Behavioral Intention ($p = 0.373 > 0.05$). In other words, the influence of initial trust on behavioral intention was relatively consistent across all age groups. This finding aligns with Kusairi et al. (2025), who stated that demographic factors, including age, do not always make a significant difference in technology adoption because usability and convenience are often perceived uniformly across generations. Similarly, Li et al. (2022) stated that efficiency, convenience, and security are more important factors than age. Boampong et al. (2022) even added that trust and reliability are

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far more dominant than demographic variables in the context of digital finance. Therefore, the results of this study reinforce the view that initial trust is a universal foundation for shaping behavioral intention, and strategies to increase trading robot adoption should focus on building trust, rather than addressing generational differences.

CLOSING

Conclusion

This study focuses on the role of initial trust and social influence in Indonesian investors' behavior toward adopting trading robots, and assesses how age moderates the relationship between initial trust and behavioral intention. Using a quantitative approach using SEM-PLS with 167 respondents, this study yields findings relevant to the context of the development of digital financial services in Indonesia. The results indicate that several factors influence the formation of investors' initial trust in trading robots. Social influence has been shown to have a significant effect, both directly on behavioral intention and indirectly through initial trust as a mediating variable. Initial trust itself plays a significant role in driving behavioral intention to use trading robots. However, age was not shown to act as a moderator, suggesting that initial trust is a stronger determinant of usage intention than age. Overall, this study confirms that initial trust and social influence are key determinants in shaping investors' intention to adopt trading robot technology in Indonesia. These factors are essential foundations for fostering the development of a more inclusive and sustainable digital financial ecosystem.

Suggestions

This study shows that initial trust and social influence are key factors in shaping investors' intention to use trading robots in Indonesia. Therefore, service providers need to emphasize transparency, security, and community support to build initial trust from the very beginning of the interaction. Regulators are also advised to strengthen public financial and digital literacy, so that investment decisions are not solely based on social opinion but are also based on a sufficient understanding of the benefits and risks of this technology. Academically, the results of this study confirm the mediating role of initial trust in the relationship between social influence and behavioral intention, while age was not shown to act as a moderator. The study's limitations lie in the limited sample size and the predominance of young respondents. Future studies could expand the demographic diversity of respondents and employ longitudinal designs or qualitative methods to capture the dynamics of investor trust more comprehensively.

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