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Determinant Intention to Adopt AI-Powered Robo Advisors

Zidane Ramadhan[1*], Umi Widyastuti[2], Meta Bara Berutu[3]
Universitas Negeri Jakarta[1,2,3]

Corresponding Author's Email: zidaneramadhan_1710621023@mhs.unj.ac.id

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ABSTRACT

Fintech in Indonesia are increasingly becoming popular, but penetration in the society is still minimal especially in investment context. This paper examines the possible drivers toward intention to adopt of AI-powered robo advisor through a modified VAM model with attitude toward using and age as moderating factors. Survey data were collected from Generation Z and millennial investors and analyzed using SEM-PLS. Our analysis shows that potential financial benefits gained from AI-powered robo advisors drives positive attitude and intention to adopt, while risk associated with AI-powered robo advisor demotivate users to adopt it. External social influences also positively impact the adoption process, demonstrating the importance of social validation in Indonesia's communal culture. Attitude toward using shows a significant performance in explaining intention to adopt AI-powered robo advisor. Moderation analysis shows that age strengthens the influence of perceived financial benefits on intention to adopt (stronger in millennials),and weakens the influence of social influence (stronger in Gen Z). These results provide theoretical and practical contributions in designing age-based marketing strategies and improving financial literacy. Future research is recommended to reach a wider demographic and conduct longitudinal studies as this technology develops

***Keywords**: AI-powered robo advisor, technology adoption, perceived financial benefit, perceived risk, social influence, age moderation, Indonesia fintech*

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INTRODUCTION

The financial technology (fintech) market in Indonesia is experiencing rapid growth along with more inclusive, efficient digital financial services. By 2023, the value of fintech transactions is expected to exceed IDR 500 trillion, a 30% increase from the previous year (Tempo, 2024). However, challenges to investing remain, particularly related to fear of loss, lack of investment literacy, and trauma from financial fraud (Prasha, 2022). Despite an increase in the number of new investors, reaching 14.81 million SID by the end of 2024 (KSEI, 2024), this number still represents a small portion of the national population. This phenomenon indicates a need for investment solutions that are more beginner-friendly, simple, and adaptable to individual risk profiles. As the solution of the newfound problem in financial management, robo advisors were founded, offering automated and personalized investment guidance, a trend that has gained global popularity since the launch of Betterment in 2010.

Robo-advisors are defined as algorithm-based systems that improves investments decision making process through data-based advisory with little human intervention (Fisch et al., 2019). In Indonesia, although several platforms such as Bibit and Bareksa have adopted this approach, most are still limited to providing advice and lack the capability to automatically rebalance portfolios tuning in with the current market movement (using prediction via AI learning model). Globally, however, the development of AI-based robo advisors shows great potential because they can dynamically manage portfolios according to market changes while offering cost efficiencies (Hou et al., 2025). AI itself has demonstrated significant market growth, particularly in the Asia-Pacific region. In the Indonesian context, adoption of this technology still faces challenges such as low financial literacy, limited user time, and a tendency towards herd behavior. Given that young investors constitute the primary demographic in capital markets (KSEI, 2024), identifying what motivates their acceptance of artificial intelligence enhanced robo advisor platforms requires thorough investigation.

Referring to previous theory on technology acceptance theory and studies, this research identifies three main factors influencing attitudes toward using and adoption intentions toward new technologies: perceived financial benefits, perceived risk, and social influence. Furthermore, demographic variables such as age play a significant role as moderating factors because each generation has different preferences and perceptions of technology (Abegao Neto & Figueiredo, 2022). This study fills the gap on technology innovations acceptance research in Indonesia, as well as providing insights on how the influence of these three factors on attitudes and intentions to adopt AI-powered robo-advisors. This research will also engage in the question of how different age could moderate these relationships. By enquiring the use of different acceptance theories, this research expands the theoretical landscape of technology acceptance as well as providing insights into the application of these theories in innovation context.

LITERATURE REVIEW

Theoretical and Conceptual Background

This study primarily adopts the Value-Based Adoption Model (VAM), because in settings like fintech, adoption is more strongly linked with cost-benefit analysis (Hong et al., 2023). This research also refers to Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) approaches to understand not just logical judgement factors, but also how emotional judgement like attitude toward using and external social pressure influences the intentions to adopt AI-powered robo advisor technology in the financial sector. Users Intention to adopt is conceptually defined as a "user desire to use the technology in the future" (Cao et al., 2020; Venkatesh et al., 2003). Theories explained that behavioural intention can be measured through planned intentions, usage expectations, and future usage preferences. This variable is significantly influenced by attitude toward use, which reflects an individual's overall emotional evaluation of the technology, noted by preference or distaste of the technology, as described by Davis (1989) and Fishbein & Ajzen (1975). This attitude is formed from user experience and perceived benefits of the technology (Su et al., 2023; Zhong et al., 2021). In the fintech context, a positive attitude toward AI-powered robo-advisors is believed to increase adoption intentions.

Perceived Financial Benefit

Perceived financial benefit is defined as " the perceived benefits an individual will experience or receive from using a robo-advisor financially" (Hong et al., 2023). Perceived financial benefit according to other research can also be stated as the perceived opportunity to save money, provide value for money, and avoid unexpected expenses through informed decision-making prior to any financial commitment (Xie & Muralidharan, 2023). The dimensions used to measure or explain perceived financial benefit in their research are perceived fees and the individual's expected return on investment (Hong et al., 2023). The relationship between perceived financial benefit and fintech adoption is clear, with individuals more likely to use innovative financial solutions when they perceive tangible economic benefits. Empirical evidence suggests that factors such as economic benefits, efficient processes, and increased trust offered by fintech services significantly influence consumers' decisions to adopt and include them in their daily life (Diana & Leon, 2020). In the context of the millennial generation, research shows a clear preference for cashless transactions driven by perceived benefits, which include the ability to transact instantly, and convenience compared to traditional banking methods (Diana & Leon, 2020).

Perceived Risk

Perceived Risk, based on research conducted by Akturan and Teczan (2012), is defined as "the risk perceived by consumers regarding the use of a technology". Akturan and Teczan (2012) explain Perceived Risk through 7 dimensions: performance risk associated with using a technology, financial risk in the form of potential loss of monetary value when using a technology, time risk in the form of lost time due to the learning process using the technology, security risk related to the potential loss of control over transaction and financial information, and privacy risk in the form of loss of control regarding personal information. They also argue that based on previous research, three key risks, that is performance, security, and financial, are sufficient to describe the potential risk perception of consumers when wanting to use technology. When discussing in the topic of robo advisor, perceived risk can be measured more specifically knowing that this technology is related to the management of customer data and finances (Hong et al., 2023).

Social Influence

Social influence, based on the UTAUT research framework by Venkatesh (2003), is defined as "the degree to which an individual is influenced by others to use a system". Accordingly, research conducted by Yeh et al. (2023) on the robo advisors acceptance in Taiwan, social influence is explained as the level which individuals perceive on others action encourage them adopt a system. Measurement of the social influence dimension usually consists of one dimension, namely through subjective norms or perceptions that environment norm is considered important on an individual's decision to use or not use a new technology.

An update to the measurement of social influence was carried out by Recskó and Aranyossy (2024) in which social influence was measured through two dimensions, that is social encouragement and subjective norm. In this context, social encouragement explains distinctly individual perception of support that will be given by those around them, and subjective norm explains exclusively the perception of the opinions or decisions of others that will encourage individuals to use a technology.

Age as a Moderator

The UTAUT2 model establishes age as a moderating variable that influences the strength of relationships between predictor and outcome variables in technology adoption scenarios (Venkatesh et al., 2003). Within this framework, age demonstrates moderating effects on the connections between social influence, price value, and consumers' technology adoption intentions (Ahsan, 2020; Merhi et al., 2020; Rahima et al., 2024). Building upon this foundation, subsequent studies have investigated age-related moderation effects across additional constructs, including perceived risk, perceived financial benefit, and usage attitudes in adoption intention models

Research conducted by Belanche et al. (2019) on robo-advisor acceptance measured age as ordinal data, where age is described through a range that has a natural order (younger to older) such as <24, 25–30, 31–40, and so on. Then, research conducted by Figà-Talamanca, Tanzì, & D'Urzo (2022) also explains age as a moderating variable with ordinal data, where age is represented through certain age groups or generations from the observations used in their research, such as generation Z and the millennial generation.

Based the comprehensive review of previous literature, we employ our conceptual research model of this study as below :

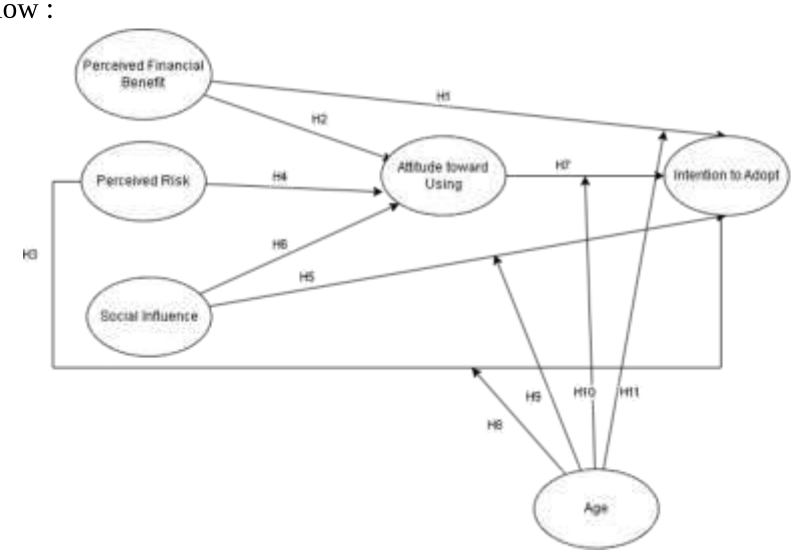

Figure 1. Conceptual Model of the Study
Source: Authors (2023)

H1:Perceived Financial Benefit positively influence Intention to Adopt AI-Powered Robo Advisors.
H2:Perceived Financial Benefit positively influence on Attitude Toward Using AI-Powered Robo Advisors.
H3:Perceived Risk acts as a main barrier toward Intention to Adopt AI-Powered Robo Advisors.

H4:Perceived Risk decreases users Attitude Toward Using AI-Powered Robo Advisors.
H5:Social Influence affect positively users Intention to Adopt AI-Powered Robo Advisors.
H6: Social Influence builds up positive Attitude Toward Using AI-Powered Robo Advisors.
H7:Attitude Toward Using positively impact users Intention to Adopt AI-Powered Robo Advisors.
H8:Age moderates the effect of Perceived Financial Benefit effect toward Intention to Adopt AI-Powered Robo Advisors.
H9:Age moderates the effect of Perceived Risk toward Intention to Adopt AI-Powered Robo Advisors.
H10:Age moderates' effect of Social Influence toward Intention to Adopt AI-Powered Robo Advisors.
H11:Age moderates the effect of Attitude Toward Using and Intention to Adopt AI-Powered Robo Advisors.

RESEARCH AND METHODOLOGY

This study employs a quantitative research approach, which is a research method that analyzes numerical data through statistical analysis. This study was conducted in Indonesia by collecting primary data through individual Google Form questionnaires. The study population was people domiciled in Jakarta, Bogor, Depok, Tangerang, and Bekasi (Jabodetabek), who were familiar with investment concepts and robo-advisors through investment applications such as Bibit or Ajaib. The researchers also selected residents of the Jabodetabek area as the sample for this study because the Jabodetabek area has the largest concentration of SID owners, according to KSEI 2024 data. Furthermore, the Jabodetabek area is an area with a high level of financial literacy regarding investment. This study used purposive sampling to recruit respondents who met all the specified criteria.

The sample criteria were as following:

1. Age range 18-44 years, following a research design focused on Generation Z and millennials, referring to research by Paramita & Cahyadi (2024), which explains that Generation Z and millennials are the dominant age groups in Indonesia in terms of fintech usage (KSEI, 2024).
2. Domiciled in Greater Jakarta (Jabodetabek), because the population of Greater Jakarta has a high level of technological literacy and, according to KSEI data (2024), is one of the regions with the highest number of SIDs.

The sample calculation uses the formula from Hair et al. (2010) with the following calculation:

$$N = 5\ until\ 10\ Observation\ x\ Total\ Indicator$$
$$N = 7\ x\ 30 = 210\ Respondent$$

Source : Hair (2010)

This study employ 6 range likert scale , a type of scale frequently used in social research. The Likert scale starts from one that represents "strongly disagree" and six representing "strongly agree." Research conducted by Chomeya (2010) showed that a six-point Likert scale can effectively measure respondents' attitudes and behaviors compared to a five-point Likert scale.

Table 1. Research Item Scale (Likert 6)

Description	Likert Scale
Strongly Disagree	1
Disagree	2
Fairly Disagree	3
Fairly Agree	4
Agree	5
Strongly Agree	6

Source : Chomeya (2010)

This study will use six variables, each of which will be further elaborated on by operational definitions. Referring to previous literature review, the operational definitions of the variables are as follows:

a) Perceived financial benefit, as the independent variable X1, measures respondents' perceptions of the financial benefits gained from using an AI-powered robo advisor. Three dimensions are used to measure perceived financial benefit: cost expenditure, perceived return, and increased investment experience.
b) Perceived risk, as the independent variable X2, measures respondents' perceptions of the risks involved in using an AI-powered robo advisor. This variable is measured through three dimensions: financial risk, security risk, and performance risk.
c) Social influence, as the independent variable X3, measures the influence of external pressures on respondents' behavior in adopting an AI-powered robo advisor. This variable is measured through two dimensions: social encouragement and subjective norm.
d) Attitude toward using an AI-powered robo-advisor, as the independent variable X4, measures individuals' attitudes toward using an AI-powered robo advisor as an investment tool. The variable measurement refers to a scale developed within the TAM theoretical framework, namely positive or negative perceptions of usage intention.
e) Intention to adopt AI-powered robo advisors as the dependent variable Y1 measures an individual's intention to adopt fintech innovation in the form of AI-powered robo-advisors. This variable is measured using one dimension, namely the individual's attitude toward using technology, based on the TAM framework.
f) As a moderator, age determines whether advancing years strengthen or weaken the links between core predictive factors (perceived financial benefits, perceived risk, social influence, usage attitudes toward AI-powered robo-advisors) and the intention to adopt this technology. Measurement derives from participant age information collected via demographic survey sections

To analyze the collected survey results, researchers will use the PLS-SEM statistical test, a multivariate data analysis method that has the advantage of measuring complex relationships between variables while still accounting for measurement errors in the indicators (Hair et al., 2022). In the SEM-PLS test, the research will conduct validity and reliability tests on the outer and inner models. Then, a bootstrapping test will be conducted to determine the hypothesis test through inference of relationship significance between variables. The operationalization of the variables refers to the following table:

Table 2. Operationalization of Variables

Variable	Dimension
Perceived Financial Benefit	*a. Perceived Fee* *b. Perceived Return* *c. Increased Investing Experience* (Sam et al., 2020; Jain & Raman, 2022 ; Filguiera et al. 2022 ; Hong et al., 2023 ; S. Fatima, M. Chakraborty, 2024
Perceived Risk	*a. Financial Risk* *b. Performance Risk* *c. Security Risk* (Bongchu Cho, 2019; Hong et al., 2023 ; Recskó and Aranyossy, 2024 ; Appiah and Agblewornu, 2025 ; Hurtado et al., 2024
Social Influence	*a. Social Encouragement* *b. Subjective Norm* (Recskó and Aranyossy., 2024)
Attitude Toward Using	*Positive peception toward using technology* (Mew & Millan, 2020)
Intention to Adopt	*User behavioral Intention to Adopt technology* (Recskó and Aranyossy, 2024)

Source: Authors (2025)

RESULT AND DISCUSSION

Result

This study involved 247 respondents spread across five regions of Greater Jakarta (Jabodetabek), with an age composition divided into two generations: Generation Z (18–28 years old) with 138 people (54.3%) and Generation Y (29–44 years old) with 109 people (45.7%). Geographically, DKI Jakarta and Bekasi were the regions with the largest representation of respondents, with 75 people (30.4%) and 66 people (26.7%), respectively. The high proportion of respondents from DKI Jakarta can be explained by its position as the economic and financial center of Indonesia with the most advanced technological infrastructure, so that its residents have higher access and exposure to fintech services (Meilasari-Sugiana et al., 2022).

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Meanwhile, Bekasi, as a satellite city of Jakarta with a large population and high urbanization rate, also shows a significant proportion, because many of its residents work in Jakarta (BPS, 2024) and are indirectly exposed to fintech services developing in the capital area (Kurniawan et al., 2024).

Table 3. Validity Test (Outer Loading)

	Perceived Financial Benefit	***Perceived Risk***	***Social Influence***	***Attitude Toward Using***	***Intention to Adopt***	***Result***
X1.1	0.866					Passed
X1.2	0.861					Passed
X1.3	0.854					Passed
X1.4	0.839					Passed
X1.5	0.864					Passed
X1.6	0.821					Passed
X1.7	0.820					Passed
X1.8	0.835					Passed
X1.9	0.846					Passed
X2.1		0.878				Passed
X2.2		0.845				Passed
X2.3		0.803				Passed
X2.4		0.835				Passed
X2.5		0.839				Passed
X2.6		0.812				Passed
X2.7		0.864				Passed
X2.8		0.842				Passed
X2.9		0.823				Passed
X3.1			0.843			Passed
X3.2			0.758			Passed
X3.3			0.853			Passed
X3.4			0.884			Passed
X3.5			0.875			Passed
X3.6			0.888	0.875		Passed
X4.1				0.923		Passed
X4.2				0.931		Passed
X4.3						Passed
Y1.1					0.886	Passed
Y1.2					0.907	Passed
Y1.3					0.903	Passed

Source: Authors (2025)

Outer loading analysis explains the reliability of indicators in explaining their latent variables in the context of the reflective model. According to Hair et al. (2022), the outer loading limit value for an indicator to be considered reliable is 0.7. The results of the outer loading analysis above show that all indicators have outer loadings above 0.7, so it can be concluded that each latent variable indicator, namely perceived financial benefit, perceived risk, social influence, attitude toward using, and intention to adopt, explains their latent variables, so that the outer loading results show valid results for all variables. Next, a reliability analysis was conducted to test differences in the consistency of the research measurement instruments.

Table 4. Reliability Test

No	Variable	Cronbach Alpha	*Average Variance Extracted (AVE)*	Criterion	Information
1.	Perceived Financial Benefit	0.950	0.828	0.600	Reliable
2.	Perceived Risk	0.948	0.808	0.600	Reliable
3.	Social Influence	0.923	0.715	0.600	Reliable
4.	Attitude toward Using	0.897	0.703	0.600	Reliable
5.	Intention to Adopt	0.881	0.725	0.600	Reliable

Source: Authors (2025)

Reliability testing evaluates the consistency of measurement instruments in capturing latent constructs accurately. The assessment employs three key metrics: Cronbach's Alpha, Rho_A, and Average Variance Extracted (AVE) coefficients (Hair et al., 2022). Results demonstrated satisfactory reliability across all measures, with Cronbach's Alpha and Rho_A coefficients spanning 0.88–0.95 (exceeding the 0.7 threshold) and AVE surpassing 0.5. These findings confirm that the five constructs—perceived financial benefit, perceived risk, social influence, attitude toward using, and intention to adopt—exhibit strong internal consistency and convergent validity (Hair et al., 2022).

Table 5. Discrimnant Validity Test

	Attitude Toward Using	Intention to Adopt	Perceived Financial Benefit	Perceived Risk	Social Influence
Attitude Toward Using	0.910				
Intention to Adopt	0.792	0.899			
Perceived Financial Benefit	0.801	0.795	0.846		
Perceived Risk	-0.068	-0.145	-0.037	0.838	
Social Influence	0.817	0.777	0.832	0.012	0.851

Source: Authors (2025)

Discriminant validity testing is a test conducted to ensure that each variable does not measure the same thing (Hair et al. 2022). The discriminant validity test table uses the Fornell-Larcker criterion, where discriminant validity is guaranteed when the Fornell-Larcker value of a variable is far greater than values in other variable. Looking at the Fornell-Larcker criterion analysis result, all latent variables values has shown greater significance in explaining their variance individually. This indicate that the discriminant validity is confirmed in this study for each variables(Hair et al., 2022). This means that each latent construct in this study truly measures a unique concept and does not overlap with other constructs, so the model can be declared discriminantly valid. Then, to measure multicollinearity, a VIF test was conducted in the form of an Inner VIF for the reflective model for all variables in the model.

Table 6. Multicolliniearity Test

	Attitude Toward Using	Intention to Adopt	Perceived Financial Benefit	Perceived Risk	Social Influence
Attitude Toward Using		**3.549**			
Intention to Adopt					
Perceived Financial Benefit	**3.272**	**3.797**			
Perceived Risk	**1.008**	**1.020**			
Social Influence	**3.268**	**4.147**			

Source: Authors (2025)

An Inner VIF (Variance Inflation Factor) analysis was conducted to determine whether there were multicollinearity issues in the model that could interfere with the model calculations (Hair et al., 2022). Multicollinearity is a condition where there is a very high correlation or linear relationship between independent variables, making it difficult to determine which variable has a greater influence on the dependent variable. Based on the analysis results, the independent variables in the research model, namely perceived financial benefit, perceived risk, social influence, attitude toward using, and intention to adopt, did not show any indication of multicollinearity because they were below the threshold of <5 (Hair et al., 2025). This indicates that each variable has a unique predictive contribution and is not highly correlated with each other. After the data was confirmed to be reliable and valid, hypothesis testing was conducted through bootstrapping.

Tabel 7. Hypothesis Testing

	Original Sample (O)	**T Statistics (|O/STDEV|)**	**P-values**	**Significance**
(H1) *Perceived Financial Benefit -> Intention to Adopt*	0.455	4.492	**0.000**	**Accepted**
(H2) *Perceived Financial Benefit -> Attitude Toward Using*	0.385	4.432	**0.000**	**Accepted**
(H3) *Perceived Risk -> Intention to Adopt*	-0.117	2.193-	**0.028**	**Accepted**
(H4) *Perceived Risk -> Attitude Toward Using*	-0.060	1.448	**0.148**	**Rejected**

(H5) *Social Influence -> Intention to Adopt*	0.213	2.707	**0.007**	**Accepted**
(H6) *Social Influence -> Attitude Toward Using*	0.497	6.058	**0.000**	**Accepted**
(H7) *Attitude Toward Using -> Intention to Adopt*	0.286	3.048	**0.016**	**Accepted**
(H8) Umur x PFB -> Intention to Adopt	0.246	3.321	**0.000**	**Accepted**
(H9) Umur x PR -> Intention to Adopt	-0.091	1.604	**0.151**	**Rejected**
(H10) Umur x SI -> Intention to Adopt	-0.159	1.746	**0.002**	**Accepted**
(H11) Umur x ATU -> Intention to Adopt	-0.129	1.134	**0.189**	**Rejected**

Source: Authors (2025)

Discussion

Perceived financial benefit positively influenced both intention to adopt and attitude toward using. This explains that users perceive the financial benefits offered by AI-powered robo advisors as the main driver of technology adoption. This explains that respondents in response of adopting AI-powered robo advisors feel that the perceived financial benefits is a very important aspect that influence their intention to adopt. This results are consistent with previous research stating that perceived financial benefits can directly shape consumers' willingness to accept a new financial technology such as AI-powered robo advisor (Liyuan et al., 2022; Hong et al., 2023; Spiga et al., 2023). Furthermore, financial benefits not only directly drive adoption intentions but also foster positive emotional responses that reinforce users' attitudes toward technology use (Liyuan et al., 2022; Hong et al., 2023; Spiga et al., 2023; Khoi et al., 2018; Filgueira et al., 2022). Thus, Hypothesis 1 and Hypothesis 2 can be accepted.

Perceived risk decreases both attitude toward using and intention to adopt, acting as a main barrier, but at different levels of significance. Regarding intention to adopt, financial, performance, and security risks become significant barriers as they prompt users to adopt a defensive stance toward technology adoption. Meanwhile, the negative influence of risk on attitude toward using is not significant, indicating cognitive dissonance, where users maintain a positive attitude toward technology use despite perceiving high risk (Festinger et al., 2017). An individual may view AI-supported robo-advisors as cool and innovative (positive attitude), yet still refuse to adopt them due to concerns about security breaches or financial losses (perceived high risk). To further explain this reason, research conducted by Sonya et al. (2018) on online shopping intentions explains that perceived risk is not significant toward attitude toward using because users are more focused on the innovation brought by technology than on perceived risk. Furthermore, the insignificant influence of perceived risk on attitude toward using, according to Sebastián et al. (2023), can be explained by the increasing familiarity of Indonesian society with digital investment technology and AI (Nugroho, 2024; Market Research Indonesia, 2025). Although AI-powered robo-advisors are still in the conceptual stage, the Jabodetabek community is already familiar with fintech and conventional robo-advisor platforms such as Bibit and Bareksa, which provide automated investment advice services. The conclusion from these results is that hypothesis 3 is accepted and hypothesis 4 is rejected.

Social influence shows a positive and significant effect on intention to adopt and attitude toward using. Social influence from the surrounding environment not only strengthens users' intention to adopt the technology but also shapes positive perceptions through the views and experiences of those around them. These results indicate that respondents feel external influences directly encourage them to use AI-powered robo-advisors. In the context of behavioral finance, social influence from friends or relatives tends to influence financial decisions, particularly in complex decisions such as investing (Venkatesh, 2003; Rizkalla et al., 2024; Terblanche & Kidd, 2022; Mew & Millan, 2021; Alryalat, 2024; Roh et al., 2024). Furthermore, social influence also affects individual perceptions, which can encourage positive or negative attitudes, in line with how other individuals perceive the use of technology. The conclusion of these results is that hypotheses 5 and 6 are accepted.

Attitude toward using shows a strong positive impact with intention to adopt, indicating that hypothesis 7 is accepted. This finding indicates that the positive attitude developed by users toward AI-powered robo advisor technology plays a strong role as a determining factor in shaping adoption intentions. This significant relationship demonstrates that when individuals have a favorable perception of the use of AI robo-advisor technology, they will show a higher tendency to adopt the technology in their investment activities. (Suhud et al., 2020; Yeh et al., 2023). Yeh et al. (2023) have proven that positive attitude toward using directly increases intention to adopt, where a positive attitude toward using a technology generally shapes a person's intention to adopt it positively. Another Research conducted by Suhud et al. (2020) on e-money adoption also supports the statement that attitude toward using has a direct impact on intention to adopt, where when users have a positive attitude toward fintech innovations driven by the benefits provided, individuals will be more motivated to accept the technology. Talking from the AI robo advisor perspective, the results explains that emotional behaviour aspect of an individual’s impacts strongly with acceptance behaviour.

An analysis of how age moderates the intention to adopt AI-driven robo-advisors reveals varying effects depending on each influencing factor. Age appears to enhance the link between perceived financial advantages and individuals’ willingness to adopt, as millennials have a more comprehensive and pessimistic approach to cost-benefit analysis compared to Generation Z, who are more optimistic and open to new technology despite perceived financial benefits not meeting expectations, thus accepting Hypothesis 8. In contrast, age diminishes the connection between social influence and the decision to adopt because Generation Z has higher FOMO (Fear of Missing Out) characteristics and tends to be more unstable, making them more susceptible to external influences and following social norms, while Millennials have a more mature and stable mindset, making them less sensitive to social pressure, thus accepting Hypothesis 10. Meanwhile, Age’s moderating role regarding perceived risk and usage attitude lacks notable statistical relevance... because both generations adopt a universal risk-averse attitude in the context of financial decisions, and attitude toward using is a cognitive confirmation consistently required by all age groups before adopting financial technology such as AI-powered robo-advisors, so hypotheses 9 and 11 are rejected

CONCLUSION

This study successfully identified drivers and barrier that shapes user’s intention to adopt innovative technology such as AI-powered robo advisors in Indonesia by testing eleven hypotheses. From the analysis results, eight hypotheses were accepted, showing that perceived financial benefits is the strongest driver toward building positive attitude toward using and intention to adopt which reflects Indonesian individuals’ behaviour seeking for potential return. In other part, social influence also shows a strong significant positive effect on both attitude toward using and intention to adopt, reflecting Indonesia's cultural characteristics of strong communal bonds where social validation is important in financial decisions. Perceived risk had a notably negative impact on the intention to adopt, as people generally prefer to steer clear of risk when making investment decisions. In contrast, attitude toward usage emerged as a strong determinant of adoption intention. Age was found to significantly moderate the link between perceived financial benefits and adoption intention—this effect was stronger among millennials. Additionally, age moderated the influence of social pressure on adoption intention, with the effect being weaker among millennials. Meanwhile, three hypotheses were rejected as insignificant: perceived risk on attitude toward using was insignificant due to increasing familiarity among Indonesians with AI technology and conventional robo-advisor platforms; the moderating effect of age on the relationship between perceived risk and intention to adopt was not significant because risk-averse attitudes are universal in financial decisions across generations; and the moderating effect of age on the relationship between attitude toward using and intention to adopt was not significant because both Generation Z and Millennials universally accept positive aspects and have relatively similar characteristics in accepting fintech related to financial decisions.

Theoretically, this study enriches innovative technology acceptance in the Indonesian fintech context by integrating the attitude toward using component from TAM and social influence to strengthen the explanation of underlying aspects that builds users intentions to adopt. Application of age moderation in VAM in the fintech investment context is still rare in Indonesia. Practically, the research findings provide strategic guidance for the fintech industry to focus on creating perceptions of benefits through competitive returns and low service costs, as well as conducting comprehensive risk assessments and age-based marketing approaches. Regulators such as the OJK and Bank Indonesia need to prepare adaptive regulations that support innovation while mitigating risks, while financial education institutions are advised to develop financial literacy curricula that integrate understanding of AI technology with approaches tailored to the characteristics of different generations.

Our study has several limitations that need to be acknowledged. First, the research sample is limited to the Jabodetabek area, which is the economic center of Indonesia, so the financial literacy level of respondents may be higher than that of people in other regions, which affect the potential widespread use of the results. Second, some research variables show discriminant validity that is close to the threshold, such as the connection between social influence and intention to adopt, indicating the need to improve indicators to create more robust validity. Third, the age moderation analysis only covers two generations, namely Generation Z and Millennials, thus failing to capture the perspectives of other generations that may have different technology adoption characteristics. Future researchers are advised to explore if attitude toward using is possible to become a sole mediator between the latent variables and intention to adopt to provide further understanding of technology adoption behaviour in Indonesia. Expanding the sample beyond Jabodetabek will enhance the applicability of the research results in wider geographical context and identifying possible strong moderating variables such as income level, financial literacy, and perceived convenience can provide granularity of this acceptance behaviour.

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