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Trust as a Mediating Factor in Enhancing Investors' Intention to Use Robo-Advising

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Abstract: Artificial intelligence (AI) has developed rapidly in recent years. Beyond its specialized domains, it has also been applied to an increasing range of other fields. Prior research suggests that traditional financial decisions are typically reached through investors' own judgment, and that such judgment is readily subject to interference from human factors and other considerations, which compromises the accuracy of the resulting decisions. In response, many developers have introduced AI into the financial industry and integrated it with investment services, giving rise to a novel form of advisory known as robo-advising, or intelligent investment advisory. Robo-advising not only breaks with the conventional human-based advisory model through AI technologies, but also helps investors make more effective decisions, thereby reducing potential losses. Existing studies have proposed that the perceived usefulness of robo-advisory technology affects users' attitude and usage intention, and that information transparency likewise affects users' attitude and usage intention, with attitude positively related to usage intention. However, relatively few studies have examined trust as a mediating mechanism through which these factors shape investors' intention to use robo-advisory. Accordingly, this study employs correlation analysis, regression analysis, and structural equation modeling to analyze the data collected from a questionnaire survey and to test the proposed hypotheses. The findings indicate that the perceived usefulness and information transparency of robo-advising are capable of establishing investor trust, and that such trust can alter investors' attitude toward robo-advising, thereby enhancing their usage intention. In addition, this study aims to offer more effective recommendations for robo-advisory technology and to support the continued development of robo-advisory investment services.

Keywords: Artificial intelligence, Robo-advising, Perceived usefulness, Information transparency, Intention to use.

1. Introduction

The development of artificial intelligence (AI) is currently a widely debated topic [1]. To date, a broad range of industries have been deeply affected by the advancement of AI [2], and its application has also become increasingly widespread in the financial sector [3]. In the emerging fintech industry, AI is combined with traditional finance with the aim of enabling investors and enterprises to create greater value together [2]. Financial markets are frequently influenced by the prevailing direction of economic development; whether the market is rising or falling, investors are nonetheless required to make decisions [4]. Robo-advising is a technology-based service built on AI that allows investors to obtain greater returns at a relatively low threshold, and it has become a popular investment decision-making model in the financial industry [5, 6].

The characteristics of robo-advising often determine whether investors adopt this model for their decisions [6]. Transparent information is one of the important factors on which investors base their strategies [3]. Declines in returns and increases in risk frequently result from information asymmetry; if unfavorable information is concealed, greater losses are likely to ensue [7]. Robo-advisory services can appropriately help investors meet their need for information transparency [8]. When people recognize the usefulness of a system, this may be described as perceived usefulness; the higher the perceived usefulness with which people evaluate a system, the more positive the attitude they form toward it [9]. Trust is likewise a critical factor in investors' decision-making behavior, and some investors, owing to their lack of trust in robo-advisory technology, tend to prefer the traditional advisory approach [9].

Research on robo-advising remains relatively limited [10]. Moreover, much of the existing literature has focused on the technology itself and on legal and security aspects, while studies conducted from the investor's perspective are comparatively scarce [2, 11]. Prior studies indicate that perceived usefulness and trust both increase people's attitude toward adopting the technology and their usage intention [9], that information transparency affects investors' attitude toward use [6], and that a positive attitude exerts a positive effect on usage intention [11]. However, few studies have examined how robo-advising, through perceived usefulness and information transparency, influences trust and thereby gives rise to usage intention. Accordingly, this study adopts the perspective of investors to investigate how robo-advising establishes a trust mechanism that produces a positive change in their attitude and, in turn, enhances their usage intention. To test the hypotheses proposed above, this study distributed questionnaires to investors and, using a quantitative analytical approach, processed and verified the collected data. The findings show that perceived usefulness and information transparency exert a positive effect on investors' establishment of trust, and that trust can enhance investors' usage intention toward robo-advising by changing their attitude. On the one hand, this study explores the factors that influence investors' intention to use robo-advising; on the other, it provides effective assistance for the improvement of robo-advisory services.

2. Literature Review

2.1. Robo-Advising

Robo-advising is a platform that uses algorithms to provide financial services to individuals [10]. Because the algorithmic mechanisms employed by AI offer greater accuracy, people tend to rely more heavily on AI technologies when making investment and trading decisions [12]. Robo-advising can, to a certain extent, compensate for the shortcomings of traditional finance and help investors achieve greater convenience [6, 9]. It is a sound choice for investors who possess limited professional knowledge and wish to obtain investment advice in a time-saving and effortless manner [6]. Compared with robo-advising, human advisors entail higher costs [10]. In terms of investment cost, investment service, and return level, robo-advising holds an advantage over traditional advisory services, enabling investors to obtain better service and higher returns at a lower cost [11]. When facing investment portfolio choices, robo-advising can also provide investors with superior portfolios [6]. Investors' investment behavior is closely related to the outcomes it produces; when market conditions fluctuate, investors may be affected emotionally, which can lead to flawed decisions. The use of AI can effectively reduce the complexity of decision-making and offer investors better decision suggestions, thereby lowering decision errors [8]. Consequently, robo-advising can also effectively avoid behavioral biases arising from emotion [10].

2.2. Perceived Usefulness

Perceived usefulness refers to an individual's subjective perception that a system can improve work performance [9]. If robo-advising can bring benefits to investors, they will be willing to adopt the technology for investment [13], indicating that users' decisions are related to the perceived usefulness of the technology [14]. In the fintech domain, perceived usefulness also changes people's recognition of, and willingness to accept, a technology [9]. Investors' acceptance of, and attitudes toward, robo-advising are inseparable from the influence of perceived usefulness, and optimizing the perceived usefulness of robo-advising is conducive to improving investors' acceptance [14]. Perceived usefulness is therefore a precondition for the development of emerging technologies [13].

2.3. Information Transparency

Transparency refers to the ability of the recommending party to explain the rationale for its recommendations when users make choices [6]. Humans may err in their judgment of data patterns or in their interpretation of them, whereas AI can identify aspects that humans tend to overlook, thereby helping investors obtain more comprehensive information [7]. Insufficient information transparency limits the application of robo-advising [3]. The more ambiguous the information investors obtain, the higher the return uncertainty they face [6]. When information asymmetry or concealment occurs, the degree of investment risk likewise increases [7]. Insufficient information transparency not only affects investors emotionally, but also influences the diffusion of robo-advising [15]. The degree of information transparency can help investors improve investment efficiency and reduce transaction errors [7].

2.4. Trust

Trust has attracted considerable attention in research on behavior [9] and constitutes the foundation of behavioral engagement [16]. It is one of the preconditions for people's willingness to accept the application and development of AI technologies [17]. In the fintech context, user trust refers to the extent to which users trust an innovative technology [5]. In the current development of intelligent technologies, trust is one of the dominant factors [17]. Many studies have proposed that when robo-advising enables investors to obtain higher returns at lower cost and with more convenient operation, their trust in it also increases [5]. Trust is a precondition for maintaining customer relationships; when investment uncertainty increases, users tend to feel insecure [5, 18]. Many people also lack trust in the technology owing to concerns about privacy protection [9]. Establishing trust can not only eliminate users' psychological barriers, but also alleviate their concerns about information privacy [5]. The higher the users' level of trust, the more readily they accept and rely on the technology [17].

2.5. Attitude and Intention to Use

Attitude denotes an individual's views and opinions toward a subject and represents the behavioral tendency formed when confronting it [9,19]. It is one of the important factors influencing individual behavior [20]. When facing decisions, those who generally maintain a positive attitude toward robo-advising are more likely to adopt it [9]. The more benefits investors derive from robo-advising, the more positive the attitude they form [11]. Attitude is therefore a key factor in individuals' acceptance of emerging technologies [19].

Behavioral intention is the condition under which individual motivation arises [19]. In investment decisions, the higher the economic returns, the more likely users are to adopt the technology and the stronger their usage intention [6]. Intention is thus a precondition for users' use of fintech [19].

Attitude and usage intention are highly interrelated [9]. Attitude significantly influences usage intention [19] and drives the formation of behavioral intention [21], and a positive attitude is a precondition for the activation of usage intention [19]. When investors hold a more positive attitude toward robo-advising, their usage intention strengthens accordingly [20]. Hence, investors' attitude toward robo-advising exerts a positive influence on their usage intention.



Figure 1. The relationship between attitude and intention to use

Sourced from the author

2.6. Research Gap

Prior studies have proposed that usage intention is closely related to perceived usefulness, and that perceived usefulness also influences the attitude toward using robo-advising [9]. The degree of information transparency can affect investors' perceptions of robo-advising [6], and usefulness and attitude jointly influence usage intention [2]. It follows that current research largely focuses on demonstrating the direct relationships between perceived usefulness and usage

intention, perceived usefulness and usage attitude, information transparency and attitude, and attitude and usage intention, whereas few studies establish trust as a mediating factor to demonstrate that perceived usefulness and information transparency can help investors build trust and thereby promote an increase in usage intention toward robo-advising. To fill the aforementioned research gap, this study aims to examine the influence of perceived usefulness and information transparency on investors' establishment of trust, the effect of trust on investors' attitude, and the effect of investors' attitude on their usage intention toward robo-advising.

3. Methods

3.1. Research Hypotheses

Through empirical testing, this study examines the effect of perceived usefulness on trust, the effect of information transparency on trust, and the effect of trust on attitude, guided by the following questions:

- To what extent does the perceived usefulness of robo-advising influence investor trust?
- To what extent does the information transparency of robo-advising influence investor trust?
- To what extent does investor trust influence investor attitude?

Based on the three questions above and drawing on the prior literature, this study proposes the following hypotheses, and Figure 2 presents the conceptual model and the related research hypotheses examined in this study:

H1: The perceived usefulness of robo-advising has a positive effect on investor trust.

H2: The information transparency of robo-advising has a positive effect on investor trust.

H3: Investor trust has a positive effect on investor attitude.

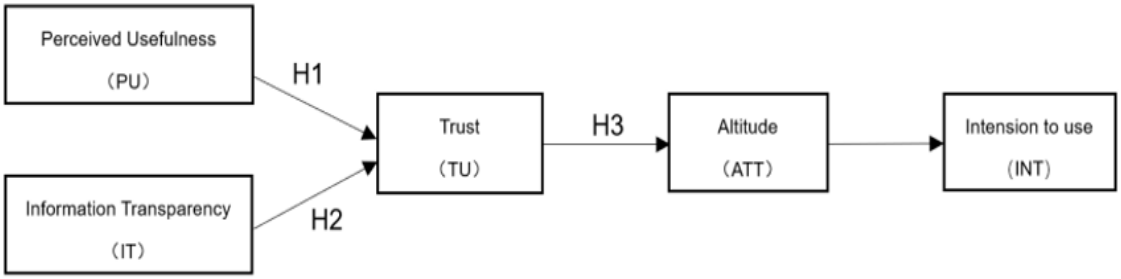


Figure 2. Conceptual model and related assumptions

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3.2. Data Collection

3.2.1. Questionnaire Survey

The five-point Likert scale is a mainstream method of statistical data collection in current academic research [22]. This study accordingly adopts a five-point Likert scale to design the questionnaire in order to test the proposed hypotheses. The questionnaire is divided into six sections. The first section asks for basic demographic information, while the remaining five sections employ the Likert scale method, with each item scored from 1 to 5, ranging from "strongly disagree" to "strongly agree," and are developed around the research theme. The second section concerns the perceived usefulness of robo-advising, the third section the information transparency of robo-advising, the fourth section investors' trust in robo-advising, the fifth section investors' attitude toward robo-advising, and the sixth section investors' usage intention toward robo-advising (for the item setting and sources, see Table 1).

Table 1. Variable Construction & Source

Latent Variables	Measurement Problem Items	Source
Perceived Usefulness (PU)	I believe that robo-advising can reduce investment risk.	(Yeh et al., 2023)
	I believe that robo-advising is helpful to me.	(Yeh et al., 2023)
	I believe that robo-advising can lower investment costs.	(Yeh et al., 2023)
Information Transparency (IT)	I believe that robo-advising can reduce information concealment.	(Irimia-Diéguez et al., 2023)
	I believe that robo-advising can gather more comprehensive information.	(Irimia-Diéguez et al., 2023)
	I believe that the information provided by robo-advising is more accessible to understand.	(Irimia-Diéguez et al., 2023)
Trust (TU)	I trust that robo-advising can provide me with better decisions.	(Arora et al., 2025)
	I trust that robo-advising can bring me higher returns.	(Arora et al., 2025)
	I feel reassured by the advice provided by robo-advising.	(Arora et al., 2025)
Attitude (ATT)	I have a positive evaluation of robo-advising.	(Yeh et al., 2023)
	Robo-advising can ease my decision-making pressure and make me feel relaxed.	(Yeh et al., 2023)
	I believe that robo-advising can bring me happiness.	(Yeh et al., 2023)
Intention to Use (INT)	I am willing to invest using the robo-advising model in the future.	(Hong et al., 2023)
	I am willing to use robo-advising for investment.	(Hong et al., 2023)
	I want to use robo-advising to invest.	(Hong et al., 2023)

Sourced from the author

The questionnaire was distributed both online and offline: online through social media platforms and offline through on-site visits, over a total collection period of one and a half months. Respondents were required to read the informed consent form before completing the questionnaire and began to answer only after confirming its contents. In total, 369 questionnaires were collected, of which 321 were valid and 48 were invalid, yielding an effective response rate of 87%.

3.2.2. Demographic Sample Analysis

Table 2 presents the demographic characteristics of the collected sample. The first part reports respondents' gender, divided into male and female. The second part reports respondents' age, comprising the ranges of 18–22, 23–27, 28–32, 33–37, and over 38 years. The third part reports respondents' educational attainment, comprising primary school, junior high school, senior high school, bachelor's degree, master's degree, and doctorate or above. The fourth part reports respondents' annual household income, comprising less than 200,000, 200,000–500,000, 500,000–800,000, and more than 800,000.

Table 2. Demographics of Main Study Sample

Characteristic	Attribute	Frequency	Percentage (%)
Gender	Male	164	51.09%
	Female	157	48.91%
Age	18-22	95	29.60%
	23-27	111	34.58%
	28-32	67	20.87%
	33-37	40	12.46%
	>38	8	2.49%
Education Level	Elementary school	2	0.62%
	Middle school	7	2.18%
	High school	43	13.40%
	Undergraduate	166	51.71%
	Graduate	86	26.79%
	Doctoral degree and above	17	5.30%
Annual Household Income (in ten thousand)	<20	154	47.98%
	20-50	88	27.41%
	50-80	61	19.00%
	>80	18	5.61%

Sourced from the author

The number of male respondents (51.09%) exceeded that of female respondents (48.91%). Because men and women differ in their thinking regarding the application of emerging technologies, men are more willing than women to adopt emerging technologies to improve returns; consequently, their intention to use robo-advising is also higher than that of women [9, 23].

The largest age group of respondents fell within the 23–27 range (34.58%), followed by the 18–22 range (29.60%), then the 28–32 range (20.87%), while respondents older than 38 formed the smallest group (2.49%). Younger groups possess higher digital cognitive ability and greater familiarity with intelligent technologies [9]. Millennials hold a relatively positive attitude toward the acceptance of AI technologies and regard robo-advising as practically valuable [21, 23]. Older investors, being more entrenched in their views than younger individuals, are less influenced by external information and opinions when investing [2].

The table shows that respondents with a bachelor's degree constituted the largest group (51.71%), while those with only a primary school education formed the smallest group (0.62%). Contemporary younger cohorts grew up in a digital environment, attained the highest levels of education, and enjoy high university enrollment rates [24]. Accordingly, most respondents had a bachelor's or master's degree, with only a minority having received less than university education.

Respondents with an annual household income of less than 200,000 ranked first (47.98%), followed by those with an income of 200,000–500,000 (27.41%), those with an income of 500,000–800,000 (19.00%), and those with an income above 800,000 (5.61%). In China, the middle-income group is defined as households with an annual income between 100,000 and 500,000 [25]. Because middle- and low-income individuals have access to fewer investment resources and obtain a limited amount of effective information, middle- and low-income households are, in comparison with high-income households, more willing to invest through robo-advising [23].

3.3. Data Analysis

3.3.1. Reliability and Validity Testing of the Measurement Model

Across different respondents and contexts, reliability is a core element ensuring that a measurement instrument stably measures the target construct [26], while validity serves as the criterion for evaluating the accuracy of research [27]. This study uses SPSS to compute the Cronbach's α values and AMOS to compute the indicator loading values; based on the computed indicator loading values, it further derives the CR and AVE values to assess the consistency and convergent validity of the data. The formulas for the composite reliability (CR) and the average variance extracted (AVE) are as follows:

Composite Reliability (CR):

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum (1-\lambda_i^2)}$$

Average Variance Extracted (AVE):

$$AVE = \frac{\sum \lambda_i^2}{n}$$

Table 3. Analysis of different latent varies

Latent Variables	Observational Variables	Indicator Loading	Cronbach's α	CR	AVE
Perceived Usefulness (PU)	PU1	0.759	0.791	0.792	0.559
	PU2	0.741			
	PU3	0.743			
Information Transparency (IT)	IT1	0.769	0.780	0.780	0.542
	IT2	0.723			
	IT3	0.716			
Trust (TU)	TU1	0.790	0.840	0.774	0.553
	TU2	0.710			
	TU3	0.687			
Attitude (ATT)	ATT1	0.694	0.804	0.719	0.462
	ATT2	0.727			
	ATT3	0.612			
Intention to Use (INT)	INT1	0.667	0.838	0.763	0.519
	INT2	0.745			
	INT3	0.746			

Sourced from the author

A CR or Cronbach's α value greater than 0.7 indicates good internal consistency of the scale [26]. Table 3 shows that the Cronbach's α values of the two variables of perceived usefulness and information transparency are all greater than 0.7, while those of the three variables of trust, attitude, and usage intention are all greater than 0.8. The CR values of the five variables are 0.792, 0.780, 0.774, 0.719, and 0.763, respectively, all greater than 0.7, meeting the criterion of good internal consistency. Regarding the AVE values, perceived usefulness is 0.559, information transparency 0.542, trust 0.553, and usage intention 0.519; only attitude, at 0.462, falls slightly below the AVE criterion, yet it remains within an acceptable range. The measurement model therefore demonstrates good reliability.

3.3.2. Correlation Analysis

Taking perceived usefulness, information transparency, trust, attitude, and usage intention as variables, this study processes and analyzes the data of the five variables using SPSS and employs Pearson correlation coefficients to reflect the relationships between perceived usefulness and trust, information transparency and trust, trust and attitude, and attitude and usage intention. To satisfy the requirement of reducing possible multicollinearity among the variables, the Pearson coefficient needs to be below 0.8 to meet the standard [28]. The results of the data analysis are presented in Table 4: all Pearson coefficients are below 0.8 and all p-values below 0.05, indicating sound correlations among the five variables.

Table 4. The correlation analysis of different varies

Varies	TU1	TU2	TU3	INT1	INT2	INT3
PU1	0.626**	0.557**	0.595**	0.576**	0.627**	0.626**
PU2	0.672**	0.566**	0.577**	0.536**	0.599**	0.603**
PU3	0.629**	0.589**	0.554**	0.569**	0.617**	0.605**
IT1	0.657**	0.613**	0.606**	0.581**	0.607**	0.633**
IT2	0.626**	0.578**	0.553**	0.528**	0.579**	0.619**
IT3	0.591**	0.578**	0.514**	0.523**	0.555**	0.588**
ATT1	0.635**	0.625**	0.581**	0.594**	0.636**	0.634**
ATT2	0.722**	0.626**	0.608**	0.581**	0.644**	0.642**
ATT3	0.599**	0.560**	0.549**	0.532**	0.609**	0.565**

Note. N=321 participants. *p<0.10, **p<0.05 ***p<0.01. From the author.

3.4. Structural Equation Modeling

This study processes the collected questionnaires and uses AMOS to construct the hypothesized model (see Figure 3) in order to test Hypotheses 1–3 and examine the pathways of the influencing factors related to robo-advising. Among the fit indices (Table 5), the χ^2 value is 335.281; the GFI, NCF, CFI, and IFI values all meet the criterion of >0.9, and the AGFI value meets the criterion of >0.8, satisfying the required fit standards. The χ^2/df value is 3.899 and the RMSEA value is 0.095; although both deviate somewhat from the standard, they remain within an acceptable range. In Table 6 showing discriminant validity results, the square roots of AVE for each latent variable are 0.736, 0.748, 0.744, 0.680 and 0.720. In Table 7, the VIF values for the two independent variables, information transparency and perceived usefulness, are both 2.315, which is lower than 5, demonstrating that serious multicollinearity is not present. Table 8 reports the standardized path coefficients of the four pathways — perceived usefulness and trust, information transparency and trust, trust and attitude, and attitude and usage intention — and the t-tests of the four paths yield values of 0.771, 0.666,

1.003, and 1.001, respectively, with all p-values below 0.01, indicating that the paths are highly significant.

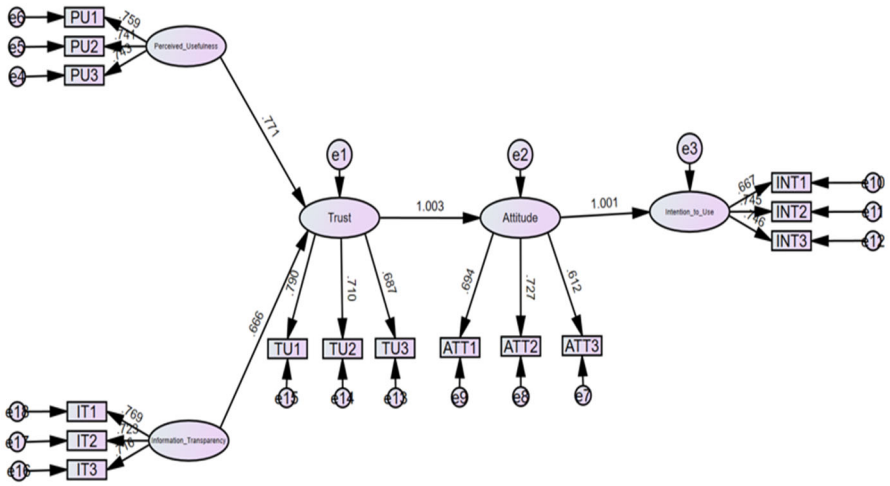


Figure 3. A preliminary model of structural equation

Sourced from the author

Table 5. Fit index value of structural equation model

Fit Indices	Recommended Value	Actual Value
χ^2	The smaller, the better	335.281
χ^2/df	<3.0	3.899
GFI	>0.9	0.909
AGFI	>0.8	0.873
RMSEA	<0.08	0.095
NFI	>0.9	0.901
CFI	>0.9	0.924
IFI	>0.9	0.925

Sourced from the author

Table 6. Discriminant Validity

	Information Transparency	Perceived Usefulness	Trust	Attitude	Intention to Use
Information Transparency	0.736				
Perceived Usefulness	0.960	0.748			
Trust	0.987	1.001	0.744		
Attitude	0.988	1.003	1.002	0.680	
Intention to Use	0.988	1.003	1.002	1.000	0.720

Sourced from the author

Table 7. Variance Inflation Factor

dependent variable	independent variable	Tolerance	VIF
Trust	Information Transparency	0.432	2.315
Trust	Perceived Usefulness	0.432	2.315

Sourced from the author

Table 8. The standardized path coefficients for the paths

Pathway	Estimate	T-value	P Value
Perceived Usefulness→Trust	0.771	11.134	***
Information Transparency→Trust	0.666	10.328	***
Trust→Attitude	1.003	11.531	***
Attitude→Intention to Use	1.001	11.264	***

Sourced from the author

3.5. Regression Analysis Results

Table 7 below presents the results of the linear regression analysis, in which trust and usage intention serve as the dependent variables and perceived usefulness, information transparency, and attitude as the independent variables. Prior research has suggested that relatively low R^2 values are acceptable in the social sciences [29]. In the table, the ANOVA p-values are all below 0.001, and both the R^2 and adjusted R^2 values exceed 0.6, with the two values being close to each other. The p-values of the relationships between the dependent variables (trust and usage intention) and the three independent variables are all below 0.001, indicating that the model is reliable.

Table 9. The analysis of regression result

Dependent Variable	ANOVA p-value	R^2	Adjusted R^2	TU (p-value)	INT (p-value)
PU	<0.001	0.666	0.665	0.816 (<0.001)	0.816 (<0.001)
IT	<0.001	0.665	0.664	0.815 (<0.001)	0.801 (<0.001)
ATT	<0.001	0.686	0.685	0.828 (<0.001)	0.819 (<0.001)

Sourced from the author

4. Conclusion

For most clients, their intention toward robo-advising is lower than toward banks, which also constitutes a challenge for the current development of fintech. To enhance users' intention, it is necessary to make changes to the robo-advisory technology itself, so as to improve its perceived usefulness and information transparency. Against the background of robo-advising, this study examines the relationship between perceived usefulness and trust, the relationship between information transparency and trust, the relationship between trust and investors' attitude, and the relationship between attitude and investors' usage intention. In the collected sample, male respondents outnumber female respondents, and most respondents are younger. This indicates that younger male groups exhibit higher acceptance of, and investment intention toward, intelligent technologies; however, in the existing literature, no consensus has been reached on the association between sustainable investment preference and investors' gender, and the degree of association between respondents' investment intention and gender may also change with the form of the survey. In the data analysis section of this study, the structural equation model constructed on the basis of the research variables and hypotheses demonstrates that perceived usefulness exerts a positive effect on trust, information transparency exerts a positive effect on trust, trust exerts a positive effect on investors' attitude, and investors' attitude is highly correlated with their intention to use robo-advising. This fully verifies that perceived usefulness and information transparency promote the formation of investor trust, that trust leads to a positive attitude, and that usage intention increases accordingly.

This study discusses the factors influencing investors' intention to use robo-advising. By treating trust as a bridge, it first explains that investor trust is influenced by the perceived usefulness and information transparency of the technology, and then establishes the pathway through which trust improves attitude and attitude raises usage intention, thereby filling the current research gap. Accordingly, the AI and financial services industries should strengthen the perceived usefulness and information transparency of robo-advisory technology, so that investors recognize that the service can help them obtain more hidden information and operational convenience and bring substantial benefits to their investment decisions and returns. In addition, with respect to information transparency, technology developers should also take information security into consideration, keeping investors' information confidential to avoid information leakage.

This study remains inadequate in exploring the factors influencing the intention to use robo-advising. First, the questionnaire survey targeted investors, and the scope of the sample is too narrow; because the distribution group is rather specific, the quality of the collected data tends to be too homogeneous. The scope of the survey should therefore be expanded so that the conclusions can be more generally applicable. Second, the respondents were investigated only through a questionnaire, which cannot fully reflect respondents' cognitions and perceptions of robo-advisory technology; focus-group interviews could be employed to make the study more convincing. Third, the processing of the collected data in this study is not sufficiently clear. Some standardized path coefficients between variables exceed the acceptable criteria. Accordingly, this paper cannot strongly verify the relationships among the five variables, and it fails to fully demonstrate that the data is free from multicollinearity issues. Finally, the hypotheses proposed in this study pertain only to the robo-advising domain and cannot demonstrate whether they also hold in other fields; the research scope should therefore be expanded so that the proposed hypotheses can be established in other domains as well. In future research, the sample population could be enlarged and focus-group interviews adopted to understand respondents' views, thereby providing further help and value for the improvement of robo-advisory technology.

References

[1] Oguntibeju, O. O. (2024). Mitigating artificial intelligence bias in financial systems: A comparative analysis of debiasing techniques. Asian Journal of Research in Computer Science, 17(12), 165–178.

[2] Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial intelligence in FinTech: Understanding robo-advisors adoption among customers. Industrial Management & Data Systems,

119(7), 1411–1430. https://doi.org/10.1108/imds-08-2018-0368

[3] Arsenault, P.-D., Wang, S., & Patenaude, J.-M. (2025). A survey of explainable artificial intelligence (XAI) in financial time series forecasting. ACM Computing Surveys, 57(10), Article 265, 1–37. https://doi.org/10.1145/3729531

[4] Anuar, A. A., Sulaiman, A. A. B., & Mohamad, M. T. B. (2025). Comparative analysis of AI-driven versus human-managed equity funds across market trends. Future Business Journal, 11(1), 95. https://doi.org/10.1186/s43093-025-00540-8

[5] Arora, S., Rajesh, A., Misra, R., & Singh, G. (2025). Bridging technology and trust: The role of AI-driven robo-advisors in middle-class financial management. Management Decision.

[6] Hong, X., Pan, L., Gong, Y., & Chen, Q. (2023). Robo-advisors and investment intention: A perspective of value-based adoption. Information & Management, 60(6), 103832. https://doi.org/10.1016/j.im.2023.103832

[7] Li, S., Younas, M. W., Maqsood, U. S., & Zahid, R. M. A. (2025). Tech for stronger financial market performance: The impact of AI on stock price crash risk in emerging market. International Journal of Emerging Markets, 20(10), 4005–4030.

[8] Hasan, Z., Vaz, D., Athota, V. S., Désiré, S. S. M., & Pereira, V. (2023). Can artificial intelligence (AI) manage behavioural biases among financial planners? Journal of Global Information Management, 31(2), 1–18.

[9] Singh, S., & Kumar, A. (2025). Investing in the future: An integrated model for analysing user attitudes towards robo-advisory services with AI integration. Vilakshan-XIMB Journal of Management, 22(1), 158–175.

[10] Isaia, E., & Oggero, N. (2022). The potential use of robo-advisors among the young generation: Evidence from Italy. Finance Research Letters, 48, 103046. https://doi.org/10.1016/j.frl.2022.103046

[11] Yeh, H.-C., Yu, M.-C., Liu, C.-H., & Huang, C.-I. (2023). Robo-advisor based on unified theory of acceptance and use of technology. Asia Pacific Journal of Marketing and Logistics, 35(4), 962–979. https://doi.org/10.1108/apjml-07-2021-0493

[12] Silber, D., Hoffmann, A., & Belli, A. (2025). Embracing AI advisors for making (complex) financial decisions: An experimental investigation of the role of a maximizing decision-making style. International Journal of Bank Marketing, 43(6), 1325–1346. https://doi.org/10.1108/ijbm-09-2024-0487

[13] Yi, T. Z., Rom, N. A. M., Hassan, N. M., Samsurijan, M. S., & Ebekozien, A. (2023). The adoption of robo-advisory among millennials in the 21st century: Trust, usability and knowledge perception. Sustainability, 15(7), 6016. https://doi.org/10.3390/su15076016

[14] Zhang, S. (2024). Consumer attitudes towards AI-based financial advice: Insights for decision support systems (DSS) and technology integration. Journal of Internet Services and Information Security, 14(4), 1–20.

[15] Maier, T., Menold, J., & McComb, C. (2022). The relationship between performance and trust in AI in e-finance. Frontiers in Artificial Intelligence, 5, 891529. https://doi.org/10.3389/frai.2022.891529

[16] Viberg, O., Cukurova, M., Feldman-Maggor, Y., Alexandron, G., Shirai, S., Kanemune, S., Wasson, B., Tømte, C., Spikol, D., Milrad, M., Coelho, R., & Kizilcec, R. F. (2025). What explains teachers' trust in AI in education across six countries? International Journal of Artificial Intelligence in Education, 35(3), 1288–1316. https://doi.org/10.1007/s40593-025-00476-9

[17] Afroogh, S., Akbari, A., Malone, E., Kargar, M., & Alambeigi, H. (2024). Trust in AI: Progress, challenges, and future directions. Humanities and Social Sciences Communications, 11(1), 1568. https://doi.org/10.1057/s41599-024-04044-8

[18] Ni, Y. (2024). The impact of explainable AI on customer trust and satisfaction in banking. Journal of Information, Technology and Policy, 2(1), 13–18.

[19] Irimia-Diéguez, A., Velicia-Martín, F., & Aguayo-Camacho, M. (2023). Predicting fintech innovation adoption: The mediator role of social norms and attitudes. Financial Innovation, 9(1), 36. https://doi.org/10.1186/s40854-023-00447-6

[20] Kim, S.-W., & Lee, Y. (2024). Investigation into the influence of socio-cultural factors on attitudes toward artificial intelligence. Education and Information Technologies, 29(8), 9907–9935. https://doi.org/10.1007/s10648-023-02612-3

[21] Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. Telematics and Informatics, 77, 101925. https://doi.org/10.1016/j.tele.2022.101925

[22] Ghorbanzadeh, D., & Rahehagh, A. (2021). Emotional brand attachment and brand love: The emotional bridges in the process of transition from satisfaction to loyalty. Rajagiri Management Journal, 15(1), 16–38. https://doi.org/10.1108/rmj-04-2020-0018

[23] Zhu, H., Vigren, O., & Söderberg, I.-L. (2024). Implementing artificial intelligence empowered financial advisory services: A literature review and critical research agenda. Journal of Business Research, 174, 114494. https://doi.org/10.1016/j.jbusres.2024.114494

[24] Selvamani, V. L., Azam, M. S., Shalini, R., & Lakshmi, J. (2026). Investigating Gen Z's equity investment intentions through a novel integrated psychological framework: An empirical validation. Acta Psychologica, 264, 106402. https://doi.org/10.1016/j.actpsy.2026.106402

[25] Xie, C., & Yang, X. (2024). Expanding the middle-income group through education: Preliminary evidence from China. ECNU Review of Education. https://doi.org/10.1177/20965311241265371

[26] Markus, A., Carolus, A., & Wienrich, C. (2025). Objective measurement of AI literacy: Development and validation of the AI competency objective scale (AICOS). Computers and Education: Artificial Intelligence, 9, 100485. https://doi.org/10.1016/j.caeai.2025.100485

[27] Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. Evidence-Based Nursing, 18(3), 66–67. https://doi.org/10.1136/eb-2015-102129

[28] Shrestha, N. (2020). Detecting multicollinearity in regression analysis. American Journal of Applied Mathematics and Statistics, 8(2), 39–42. https://doi.org/10.12691/ajams-8-2-1

[29] Ozili, P. K. (2023). The acceptable R-square in empirical modelling for social science research. In C. Saliya (Ed.), Social research methodology and publishing results: A guide to non-native English speakers (pp. 134–143). IGI Global Scientific Publishing. https://doi.org/10.4018/978-1-6684-6859-3.ch009