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Investor Decision-Making in Robo-Advisory Services: A Trust-Mediated Perspective

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ABSTRACT

Robo-advisory services offer automated, algorithm-based investment advice and portfolio management, enabling cost efficiency and wider access to financial services. Despite these advantages, adoption in emerging economies remains limited due to psychological, cognitive, and social barriers. Trust is particularly critical in financial decision-making, as it reduces perceived risk and uncertainty associated with algorithm-driven systems. Trust is an important component, since adoption depends on people's faith in technological advances and the safety of their investments. The study purposes to contribute to the larger in the field of financial technology analysing the factors which impact on the adoption of Robo-advisory services and provide new insights into the psychological and social dynamics. Using a quantitative research design, primary data were collected from 285 investors through a structured questionnaire. Partial Least Squares-Structural Equation Modeling (PLS-SEM) was employed to test the proposed relationships among financial awareness, behavioral biases, innovativeness, subjective norms, trust, and intention to use robo-advisory services. The results indicate that trust is the strongest predictor of adoption intention and significantly mediates the effects of key antecedent variables. The findings could help policy-makers and financial institutions to enhance the features of robo-advisory services with targeted interventions and marketing strategies.

Introduction

Financial technology, also known as fintech, has significantly altered how individuals and organizations engage with financial markets. One of the most disruptive developments in fintech in recent years has been the emergence of robo-advisory services, which are automated digital platforms that provide algorithm-based investment advice(Ramesh et al., 2023). Robo-advisors have become very popular all over the world since the early platforms, like Wealthfront and Betterment, were introduced in the US around 2008. By 2025 asset under management (AUM) in the robo-advisors market is projected to reach US$ 2.06 trillion (Statista, 2025) demonstrating quick investor acceptance in developed nations like the United States, the United Kingdom, and some European

countries. These services are intended to revolutionize the wealth management sector by lowering expenses, minimizing human biases, offering personalized portfolio recommendations, and democratizing access to financial planning. In India AUM in Robo-advisory market are projected only US$ 23 billion as compared to global market which is hardly 1.2% of global market (Statista, 2025) which is a clear indication of slower growth in comparison to global benchmarks. Digital investment platforms such as Scripbox, ET Money, Groww, Kuvera and Paytm Money have introduced Indian investors to a greater extent of automated financial advice. However, the adoption rates are still lower in developed markets. Factors such as low financial literacy, reliance on traditional intermediaries (relationship managers, banks, and brokers), resistance to technology and a culture of personalized advice are still influencing the adoption process.

The presence of trust is observed in the literature on technology adoption. In cases of sensitive decisions, such as financial investments, trust will make people feel more comfortable with automated systems, as it will reduce uncertainty and perceived risks (Bruckes et al., 2019). Unlike the traditional advisory services, robo-advisors are totally devoid of the human touch and leave all decisions to algorithms. Investors who are accustomed to face-to-face communication and customised advice are already predisposed to a lack of trust (Schütz et al., 2023). Therefore, trust can be considered as a mediator in the process of converting social, cognitive and individual factors into behavioral intentions, as well as being a predictor of adoption. Technology Trust Theory (TTT) states that trust is a key element in the relationship between humans and technology. But in the financial services sector, where there are plenty of risks and uncertainties, trust is even more critical (Singh & Kumar, 2024). Investors need to think that the system is capable, trustworthy, safe, and in line with their interests. Research on mobile payments, e-commerce, and digital banking constantly emphasizes how trust acts as a mediator in adoption. However, there is still a dearth of empirical research on robo-advisory services in developing markets, particularly in Punjab and other similar regions.

Few studies have looked at trust's mediating role in the adoption of robo-advisory services in India, despite the fact that trust is a key determinant in the global literature on fintech adoption. Without evaluating comprehensive models, the majority of studies either treat trust as a direct predictor or concentrate on specific antecedents (Cheng et al., 2019; Eren, 2024; Guo et al., 2019). Furthermore, there are few regional studies, even though cultural, educational, income, and investment preferences cause financial behavior in India to differ significantly between states (G Nair & S. Chakkambath, 2024; Shiva et al., 2023). The unique socio-economic structure of Punjab has not received much attention in this context. Despite the potential of democratised, cost-effective and bias-free investing, two challenges limit the use of robo-advisory services in emerging economies investors do not trust algorithms to make financial decisions and the service is not well known. This study explores the antecedents and mediating effect of trust in the process of financial inclusion, aiming to help stakeholders bridge this trust gap and accelerate the financial inclusion process by leveraging digital innovation.

Objectives of the Study

1. To examine the influence of factors on trust in the adoption of robo-advisory services in Punjab, and subsequent effect of trust on investors' intentions to adopt these services.
2. To investigate the mediating role of trust in the relationship between these factors and investors' intention to utilize robo-advisory services.

Literature Review

Trust is a significant element in consumer decision making, particularly when the decisions are made in risky and uncertain circumstances. Confidence in robo-advisory services involves beliefs about algorithmic accuracy, transparency, privacy and security of data, and legitimacy of the institution. Previous studies have demonstrated how important trust is to the adoption of fintech. Brückes et al. (2019) found that initial trust was a significant factor in the adoption of robo-advisors, with structural assurances enhancing trust and risk reducing it. What was notable is that the trust in banks was only found to lead to trust in robo-advisors when no structural assurances were present. They found that while consumers were willing to take risks, adoption was indeed very dependent on trust. Cheng et al. (2019) used a mixed-method approach to investigate how trust influences robo-advisory services. Six key factors impacting trust were identified: government regulation, attitude towards AI, information quality, service quality, service commitment, and reputation. Their findings highlighted the differences between junior and senior investors in developing trust towards robo-advisors, and lent support to the role of trust transfer theory. To explore the factors that impact trust in robo-advisor products, Guo et al. (2019) interviewed 27 investors using semi-structured interviews. The study found six major factors, which included 18 sub-factors namely benefits, regulations, customer characteristics, vendor characteristics, service quality and external environment. They put forth a conceptual framework that shed light on how various investor types, from inexperienced to seasoned developed confidence in robo-advisors.

Hildebrand and Bergner (2021) explored how robo-advisors impacted financial services consumers' trust and decision-making. It also brought up concerns regarding reduced accountability and transparency. The dual function of robo-advisors as technologies that both challenge and enhance trust was highlighted by their findings. Amnas et al. (2023) used TAM to examine Pakistani investors' intentions to use robo-advisors. Perceived usefulness and ease of use had a significant impact on the intention to adopt, and perceived risk and trust were found to be mediators. Their results pointed to the need for financial institutions to increase trust and reduce uncertainty to enable wider adoption. Performance expectancy, effort expectancy, and trust were found to have significant effects on adoption intentions, with perceived risk having a negative effect, as revealed by Ashrafi et al. (2023). Their results made clear how crucial it is to increase user confidence and reduce ambiguity in order to increase robo-advisory adoption. Nguyen et al. (2023) investigated the variables affecting Malaysians' acceptance of robo-advisors. The findings showed that perceived risk did not have a significant impact while relative advantage, effort expectancy and social influence had a positive effect on users' behavioral intention to adopt Robo-Advisors. Tan Zi Yi et al. (2023) examined the adoption of robo-advisors among millennials in Malaysia, focusing on perceptions of usability, trust, and financial literacy. The study discovered that millennials' propensity to use robo-advisory services

was highly impacted by all three of these factors. The findings highlighted the need for trust-building and financial education to facilitate sustainable FinTech adoption.

Aqil et al. (2024) discovered that social influence, performance expectancy, and trust propensity were important variables affecting people's initial trust in robo-advisors. Their findings highlighted the importance of considering psychological and social aspects of automated investment platforms to foster greater adoption. Cao et al. (2025) concluded that acceptance was hampered by perceived risk, but adoption intention was positively impacted by perceived utility, usability, and institutional trust. They found that the institutional trust needs to be boosted and the risk perceptions lowered if they are to expand robo-advisory services.

Theoretical Framework

Social, technological and psychological factors play a huge role in the adoption of robo-advisory services, particularly in developing countries such as India. Although conventional models such as the Theory of Planned Behavior (TPB), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM) and TTT provide valuable insights into user acceptance, they often fail to consider the important mediating role of trust between behavioral intention and user characteristics. Trust is the key psychological mechanism that translates independent factors like behavioral biases, innovativeness, financial awareness, and subjective norms into actual intentions to adopt robo-advisory platforms in the financial services industry, where there is a high degree of uncertainty, risk, and information asymmetry. The TAM (Davis, 1989) has identified perceived usefulness (PU) and perceived ease of use (PEOU) as important factors in the adoption of technology. TAM has been tested across a number of areas including in online banking and in digital commerce (Venkatesh et al., 2012). In financial technology, however, TAM is less applicable in that it does not incorporate trust, which often is a factor in adoption (Gefen et al., 2003). UTAUT (Venkatesh et al., 2003) is an expansion of TAM and includes elements from various adoption theories. It focuses on factors affecting the use of technology: social influence, performance expectancy, effort expectancy, enabling circumstances. In collectivist societies such as India, social factors play a significant role in influencing financial behaviors, making social influence particularly strong. TPB (Ajzen, 1991) provides greater detail, and includes attitude, subjective norms and perceived behavioral control as determinants of behavioral intention. Particularly TPB is relevant to this study because subjective norms (social pressures and approbation) are good predictors of financial behaviors in the social context of Punjab. TPB (or similar models like TAM and UTAUT) fail to account for the gain or loss of trust in automatic systems, particularly in critical financial situations. Scholars have looked to models that specifically incorporate trust in recognition of this limitation. TTT (McKnight et al., 2011) defines trust in technology systems as competence (the ability to deliver reliable outcomes), integrity (accuracy and fairness), and benevolence (acting in the user's best interests). TTT provides clarity on the decision of whether or not investors will rely on robo-advisors to make financial decisions. The frameworks are aligned with the notion that trust is a mediator between behavioral intention to use robo-advisory services and other factors such as behavioral biases, innovativeness, financial awareness, and subjective norms. This synthesis not only ensures theoretical rigor and contextual relevance but also captures the specific dynamics of fintech adoption in Punjab.

Conceptual Framework

Financial Awareness, Trust and Intention to use

Financial literacy and financial awareness are closely related terms that describe people's knowledge and comprehension of financial concepts and products. Investors who are more financially literate are better able to recognize the potential advantages of robo-advisory services(Ashrafi, 2023), including cost effectiveness and diversification (Lusardi & Mitchell, 2014). However, awareness needs to be paired with faith in the integrity and dependability of the technology (Yi et al., 2023). If they don't trust algorithm-driven recommendations, even financially savvy investors might not adopt them. In this context, the study proposes the following hypothesis:

Hypothesis 1a. Financial literacy positively influences the Trust.

Hypothesis 1b. Financial literacy positively influences the Intention to use.

Hypothesis 1c. Trust mediates the relationship between financial literacy and Intention to use.

Subjective Norms, Trust and Intention to use

Subjective norms, which are derived from TPB, represent the perceived social pressure to engage in or refrain from engaging in a specific behavior (Ajzen, 1991). Subjective norms have a significant impact in collectivist societies, especially when it comes to money, where decisions are frequently justified by the approval of peers and family (Belanche et al., 2019). Social validation is a major factor in adoption of fintech applications and other forms of technology (Jisham et al., 2024). However, adoption of subjective norms might only occur if trust is built; without internal confidence in the technology's competence and integrity, external endorsement is unlikely to be sufficient. The hypothesis formed as:

Hypothesis 2a. Subjective Norms positively influences the Trust.

Hypothesis 2b. Subjective Norms positively influences the Intention to use.

Hypothesis 2c. Trust mediates the relationship between Subjective Norms and Intention to use.

Innovativeness, Trust and Intention to use

Innovativeness is a reflection of people's readiness to experiment with new technologies (Flavián et al., 2022). Investors with a high level of innovation are more likely to use digital financial tools like robo-advisors. Innovation by itself, though, might not ensure adoption; if these people believe the technology is unreliable or prone to mistakes, their willingness to adopt will decline (Wu & Peng, 2024). Therefore, innovativeness primarily affects trust, which in turn affects behavioral intention.

Hypothesis 3a. Innovativeness positively influences the Trust.

Hypothesis 3b. Innovativeness positively influences the Intention to use.

Hypothesis 3c. Trust mediates the relationship between innovativeness and Intention to use.

Behavioral Biases, Trust and Intention to use

Behavioral finance studies demonstrate that the psychological factors of overconfidence, loss aversion, herding, and anchoring can impact investors and that they may not be as rational as they believe (Shiva et al., 2023). These biases often affect the decision-making process in a manner that deviates from economic prediction. Biases can either promote or hinder adoption in the context of robo-advisory adoption. For example, overconfident investors may not want to use automated advice, while risk-averse investors may want to use robo-advisors because they offer data-driven, disciplined advice (Bhatia et al.,2020). Perhaps most importantly, these biases need to be overcome by trust in order to be transformed into adoption behaviors: investors must believe that robo-advisors can overcome their own cognitive biases and deliver better performance.

Hypothesis 4a. Behavioral biases positively influences the Trust.

Hypothesis 4b. Behavioral biases positively influence the Intention to use.

Hypothesis 4c. Trust mediates the relationship between Behavioral biases and Intention to use.

Trust and Intention to Use

It is commonly acknowledged that trust is a crucial factor in determining the adoption of technology (Gefen et al., 2003; McKnight et al., 2002). Because investors must entrust decision-making to algorithms in situations involving financial risk, like robo-advisory services, trust becomes even more crucial (Bashir et al., 2025). Research demonstrates that trust has a major impact on behavioral intention in digital wallets, AI-based investment platforms, and mobile banking. Therefore, trust is anticipated to have a similar function in the robo-advisory context. Trust serves as the primary mechanism via which antecedents minimize uncertainty and risk.

H5. Trust has a positive effect on Intention to use Robo-advisory services.

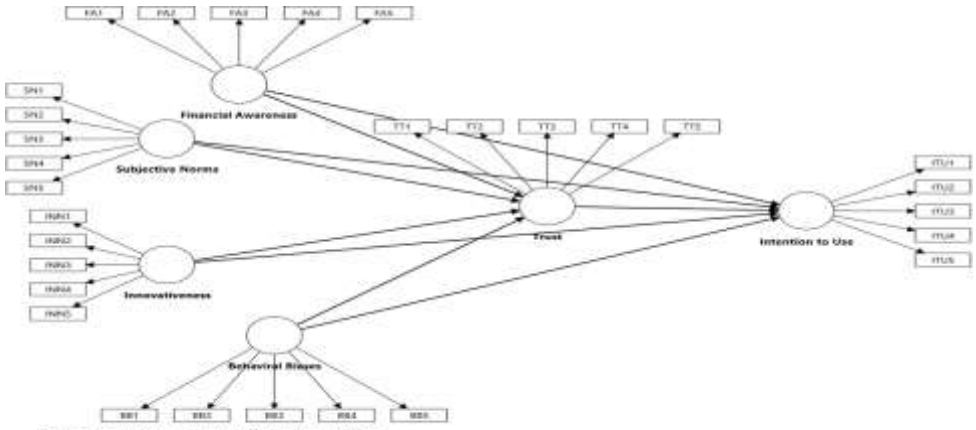


Fig 1: Proposed conceptual model

Research Methodology

Research Design

The current study uses a quantitative and explanatory research approach to evaluate the effect of trust on investors' behavioral intention to use robo-advisory services in Punjab. This approach highlights the method used in previous studies ((Bashir et al., 2025; Eren, 2024).The explanatory

design was used because the study aims to investigate hypothesized links between antecedent variables (behavioral biases, innovativeness, financial awareness, subjective norms), the mediating construct (trust), and the dependent variable. Quantitative design is appropriate because the constructs are operationalized into measurable indicators and analysed using structured questionnaires, allowing statistical modelling approaches like Partial Least Squares Structural Equation Modelling (PLS-SEM) to be applied.

Data Collection and Sampling

The study used a structured questionnaire to gather primary data from Punjabi retail investors, mainly focused on people who were familiar with digital financial platforms. Respondents were contacted offline (at workshops, brokerage houses, and financial institutions) and online (through Google Forms, email, and investment groups). A purposive sampling technique was used to guarantee relevance, focusing on investors who were exposed to or aware of robo-advisory services(Cao et al., 2025). Using G*Power software, the sample size was calculated, with a power of 0.80 (Faul et al., 2009). The minimum sample size at significance level 5% and effect size 0.05 is 159. So, considering the minimum level, the data is collected from 285 investors, which found appropriate for the study. A pilot study has been done on 30 investors to check the reliability and validity of questionnaire.

Research Instrument

A structured questionnaire is prepared by using the studies (Alamayreh et al., 2023; Ansari & Bansal, 2024; Flavián et al., 2022; Shiva et al., 2023) for the factor related questions. The questionnaire comprises two sections. Second part constitute the investors' demographic variable related general questions on Age, Gender, Qualification and Income etc. First is a main part which includes the Robo-advisory related inquiries of the investors and questions covers the measurement of the factors. In this case, everything was rated on a Five-point Likert scale, with 1 being "strongly disagree" and 5 being "strongly agree."

Method of Estimations

This study uses PLS based SEM by using the software smart PLS 4 for confirmatory factor analysis (CFA-SEM) and hypothesis testing. SEM is used to analyse complex interactions between numerous latent variables, making it suitable for verifying the study's theoretical framework (Dash & Paul, 2021). PLS-based SEM is ideal for small to medium sample sizes, non-normal data distributions, and exploratory research focusing on theory construction and prediction(Hair et al., 2017) . Further, this study aims to examine how investor perceptions and behavioral intentions differ. PLS-SEM with composites is more effective than CB-SEM for analysing and assessing complex setups with many measurement limitations in a factor model. The measurement model is validated using PLS-based SEM, which assesses outer model loadings, VIF, convergent validity, and discriminant validity (Hair et al., 2019). The structural model is evaluated to test hypotheses and draw conclusions about variable correlations using model fit indices, path coefficients, and significance levels. Variance-based SEM strengthens research model analysis and improves findings dependability (Hair et al., 2019; Zhao et al., 2010).

Data analysis

Demographic information

Table 1 shows the information related to demographic variables of investors. This shows that 63% are male and 36% are female among the investors. 21% belongs to age limit between 20-29, 35% belongs to 30-39, 30% are between 40-49 and only 12% are above 50 years of age. In relation to occupation, mostly persons are salaried which app.61% whereas, 27% are professionals and 11% are businessman. Majority of persons have income between 250000-750000 per annum in Rupees which are app. 34% and 36%. Investors who posse any graduate and post-graduation degrees are 27% and 29% approximately, whereas, 15% are Ph.D. holder and 19% are under-graduate.

Table 1 Demographic Profile of Investors

Features	Total	Percentage	Features	Total	Percentage
Gender			**Income**		
Male	181	63.5	Less than 250000	35	12.3
Female	104	36.5	250001-500000	97	34.1
Age			500001-750000	103	36.1
20-29	62	21.8	More than 750000	50	17.5
30-39	102	35.7	**Qualification**		
40-49	86	30.2	Under Graduate	56	19.7
Above 50	35	12.3	Graduate	79	27.7
Occupation			Post-Graduate	85	29.8
Salaried	175	61.4	Ph.D.	45	15.7
Business	32	11.2	Others	20	7.1
Profession	78	27.4			

Measurement Model Assessment

Table 2 shows the indicator reliability of all latent constructs, composite reliability (RhoA, composite reliability) and Average Variance extracted (AVE) showing convergent validity. These measurement evaluations follow the guidelines for threshold values under Hair et al., 2019. Loading above 0.70, Cronbach's alpha above 0.70, composite reliability above 0.70, and AVE above 0.50" (Hair et al., 2022) indicates that the internal consistency is excellent. All values of the table meet the requirement except one item (Innovativeness5) whose outer loading 0.68 that retain while further analysis because AVE is more than the threshold value 0.5.

Table 2 Construct Reliability and Validity

Factors	Outer loadings	Cronbach's alpha	rho_a	Composite reliability	AVE
Behavioral Biases		0.868	0.871	0.904	0.654
BB1 <- BB	0.743				
BB2 <- BB	0.847				
BB3 <- BB	0.782				

BB4 <- BB	0.827				
BB5 <- BB	0.841				
Financial Awareness		0.872	0.879	0.908	0.663
FA1 <- FA	0.8				
FA2 <- FA	0.82				
FA3 <- FA	0.841				
FA4 <- FA	0.861				
FA5 <- FA	0.744				
Innovativeness		0.8	0.812	0.862	0.557
INN1 <- INN	0.721				
INN2 <- INN	0.828				
INN3 <- INN	0.788				
INN4 <- INN	0.705				
INN5 <- INN	0.681				
Subjective Norms		0.879	0.88	0.912	0.674
SN1 <- SN	0.815				
SN2 <- SN	0.792				
SN3 <- SN	0.826				
SN4 <- SN	0.828				
SN5 <- SN	0.844				
Trust		0.851	0.853	0.893	0.627
TT1 <- TT	0.742				
TT2 <- TT	0.831				
TT3 <- TT	0.816				
TT4 <- TT	0.793				
TT5 <- TT	0.773				
Intention to Use		0.868	0.872	0.904	0.655
ITU1 <- ITU	0.831				
ITU2 <- ITU	0.761				
ITU3 <- ITU	0.805				
ITU4 <- ITU	0.814				
ITU5 <- ITU	0.832				

The heterotrait-monotrait (HTMT) ratio in **table 3** shows the discriminant validity which evaluated correlation between constructs. The findings confirmed adequate discriminant validity, with the majority of construct pairs exhibiting HTMT values significantly below the conservative threshold of 0.85 (Henseler et al., 2015). Higher correlations were found between Trust–Financial Awareness (0.864), Financial Awareness–Behavioral Biases (0.87), and Trust–Intention to Use (0.852), which fell short of the more widely used 0.90 cut-off but marginally surpassed the more stringent 0.85 threshold (Hair et al.,2022). These results further checked by bootstrapping using 10000 subsamples,

discriminant validity was supported by the fact that the value of 1 was excluded from the confidence intervals for all HTMT values. HTMT values 0.85 also checked within the lower bound and upper bound of confidence intervals at 95 percent considered an appropriate technique (Hair et al.,2022). These two limits explain the discriminant legitimacy of the above Trust–Financial Awareness (0.864), Financial Awareness–Behavioral Biases (0.87), and Trust–Intention to Use (0.852).

Table 3 Discriminant Validity

HTMT Correlations between constructs	HTMT	Confidence Intervals	
		2.50%	97.50%
Financial Awareness <-> Behavioral Biases	0.87	0.807	0.925
Innovativeness <-> Behavioral Biases	0.448	0.29	0.595
Innovativeness<-> Financial Awareness	0.472	0.288	0.648
Intention to Use <-> Behavioral Biases	0.624	0.494	0.732
Intention to Use<-> Financial Awareness	0.769	0.661	0.856
Intention to Use <-> Innovativeness	0.443	0.282	0.593
Subjective Norms <-> Behavioral Biases	0.632	0.508	0.74
Subjective Norms <-> Financial Awareness	0.694	0.576	0.789
Subjective Norms<-> Innovativeness	0.418	0.245	0.583
Subjective Norms <-> Intention to Use	0.611	0.469	0.731
Trust<-> Behavioral Biases	0.812	0.731	0.873
Trust<-> Financial Awareness	0.864	0.793	0.916
Trust <-> Innovativeness	0.53	0.353	0.705
Trust<-> Intention to Use	0.852	0.776	0.916
Trust <-> Subjective Norms	0.686	0.557	0.795

Source: Smart PLS 4

Structured Model Assessment

According to the outcomes of the structural model **Table 4 and Fig.2**, trust plays a crucial role in influencing adoption behavior and is the most significant determinant of intention to use ($\beta = 0.506$, $p < 0.001$). The dual importance of financial awareness is highlighted by the significant positive direct effect it has on intention ($\beta = 0.294$, $p = 0.004$) and its strong contribution to trust ($\beta = 0.403$, $p < 0.001$). Behavioral biases, innovativeness, and subjective norms, on the other hand, have a positive impact on trust ($\beta = 0.247$, $p < 0.001$; $\beta = 0.133$, $p = 0.009$; $\beta = 0.166$, $p = 0.005$, respectively), which makes their influence on intention clear. These relationships are further supported by effect size analysis, which shows that Trust had the largest impact ($f2 = 0.231$) and Financial Awareness had the moderate impact ($f2 = 0.168$), with the other predictors showing only small effects. Furthermore, mediation analysis **table 5** showed that the relationships between all four predictors and ITU were significantly mediated by trust. FA had the largest indirect effect ($\beta = 0.203$, $p < 0.001$), followed by BB ($\beta = 0.126$, $p = 0.001$), SN ($\beta = 0.085$, $p = 0.010$), and INN ($\beta = 0.067$, $p = 0.011$). These results demonstrate that although financial awareness can have a direct or indirect impact on ITU, trust is

necessary to fully realize the effects of behavioral biases, innovativeness, and subjective norms. Furthermore, mediation analysis showed that the relationships between all four predictors and ITU were significantly mediated by trust. FA had the largest indirect effect (β = 0.203, p < 0.001), followed by BB (β = 0.126, p = 0.001), SN (β = 0.085, p = 0.010), and INN (β = 0.067, p = 0.011). These results demonstrate that although financial awareness can have a direct or indirect impact on ITU, trust is necessary to fully realize the effects of behavioral biases, innovativeness, and subjective norms. So, financial awareness maintained an indirect path through trust and a significant direct path to intention to use, indicating partial mediation. On the other hand, full mediation was evident in the effects of behavioral biases, innovativeness and subjective norms on intention to use, which were only significant through trust and not through their direct paths

Table 4 Structural model assessment results (Direct effect)

Hypothesis	**Path**	**Mean**	**ST.DEV**	**t-value**	**P values**	**C.I. [2.5:97.5]**	**Significance (p < 0.05)?**	**VIF**	**f^2**
H:1a	FA -> TT	0.403	0.065	6.334	0.000	[0.277:0.530]	Yes	2.71	0.168
H:1b	FA -> ITU	0.294	0.102	2.909	0.004	[0.088:0.492]	Yes	3.16	0.068
H:2a	SN -> TT	0.166	0.058	2.823	0.005	[0.050:0.277]	Yes	1.66	0.044
H:2b	SN -> ITU	0.096	0.055	1.699	0.089	[-0.011:0.204]	No	1.73	0.012
H:3a	INN -> TT	0.133	0.048	2.607	0.009	[0.039:0.225]	Yes	1.23	0.035
H:3b	INN -> ITU	0.034	0.039	0.825	0.409	[-0.041:0.111]	No	1.27	0.002
H:4a	BB -> TT	0.247	0.063	3.954	0.000	[0.127:0.376]	Yes	2.43	0.07
H:4b	BB -> ITU	-0.089	0.078	1.153	0.249	[-0.234-0.072]	No	2.6	0.008
H:5	TT -> ITU	0.506	0.061	8.286	0.000	[0.389:0.629]	Yes	2.73	0.231

(Note: FA-Financial Awareness; SN-Subjective Norms; INN-Innovativeness; BB-Behavioral Biases; TT-Trust; ITU-Intention to Use)

Table 5 Indirect path for mediation effect

Indirect Path	Mean	ST.DEV	t-value	P values	C.I. [2.5:97.5]	Significance (p < 0.05)?
SN -> TT -> ITU	0.085	0.032	2.569	0.010	[0.026:0.153]	Yes
BB -> TT -> ITU	0.126	0.038	3.364	0.001	[0.062:0.211]	Yes
FA -> TT -> ITU	0.203	0.039	5.337	0.000	[0.138:0.293]	Yes
INN -> TT -> ITU	0.067	0.025	2.557	0.011	[0.021:0.118]	Yes

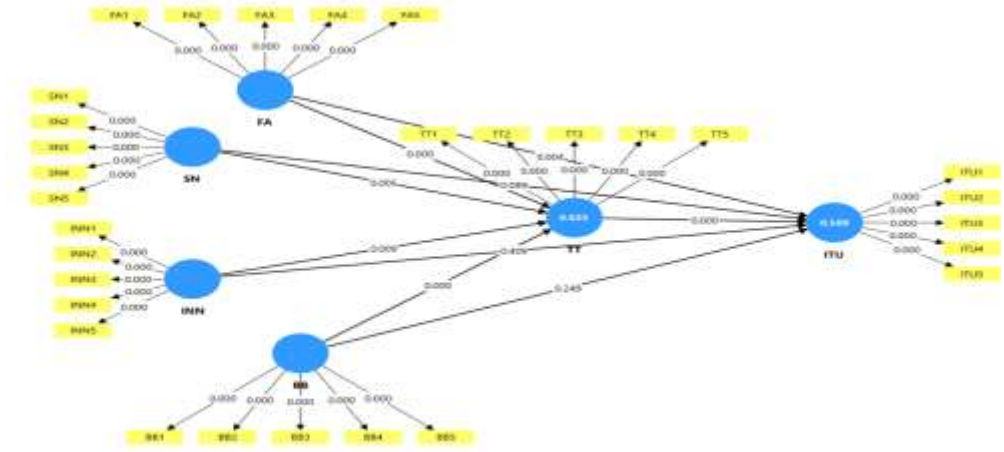


Fig2: Results of assessment of structural model

Table 6 Model fit Indices

	Saturated model	Estimated model
SRMR	0.077	0.077
d_ULS	2.793	2.793
d_G	1.903	1.903
Chi-square	2619.041	2619.041
NFI	0.62	0.62

The structural model has an acceptable degree of adequacy, according to the model fit evaluation according to table 6. The SRMR value of 0.077 indicates a good approximate fit because it is less than the suggested cutoff of 0.08 (Henseler et al., 2015). The differences between the empirical and model-implied covariance matrices are further confirmed to be within acceptable bounds by the discrepancy measures d_ULS (2.793) and d_G (1.903). Given the sample size and complexity of the model, the chi-square statistic (2619.041) is expected to be relatively high and is therefore not regarded as problematic in PLS-SEM (Hair et al., 2021). Crucially, the results for the saturated and estimated models are identical, demonstrating the structural model specification's internal consistency.

Fig 2 represent that the model explains a significant amount of variance in the endogenous constructs, according to the R2 results, which indicate explanatory power. With an R2 of 0.633 (adjusted R2 = 0.628), Trust (TT) has a significant explanatory power, with its predictors accounting for roughly 63% of its variance (Hair et al., 2021). Similarly, the R2 for Intention to Use (ITU) is 0.589

(adjusted R2 = 0.582), indicating that Trust, Financial Awareness, Behavioral Biases, Subjective Norms and Innovativeness explain about 59% of the variance in ITU. Overall, the results indicate that the model is suitable for hypothesis testing, as it provides a good fit and has a high explanatory power.

Discussion and implications

The study results offer a comprehensive body of evidence as to what factors affect robo-advisor adoption. The measurement model was found to be reliable and valid with HTMT of less than 0.90 (Henseler et al., 2015), indicating the presence of discriminant validity. The results of structural model revealed that behavioral biases and innovativeness did not directly predict intention but had significant indirect effects on intention through trust, which showed a mediating effect. The results of the mediation confirmed partial mediation, indicating that trust transmits the influence of psychological and contextual factors into adoption behaviours. According to the findings, the foundation of robo-advisory adoption is user trust, which is influenced by awareness, social influence, and behavioral prejudices. Behavioral biases influence the adoption intention through trust which further extension of previous study (shiva et al.,2023) which shows behavioral biases has no direct effect on intention to use the Robo-advisory services. In addition to extending knowledge of how innovativeness interacts to shape adoption decisions, this is also consistent with earlier research that highlighted trust as a key determinant in the adoption of financial technology (Flavián et al.,2021). In order to better understand how consumers who are sensitive to financial information accept and use the technological activation attributes, this study verified different mediating approaches to trust through a post-hoc analysis also confirmed in previous studies (Roh et al., 2023).

Theoretical Implications

The present study makes several significant theoretical advances. It reaffirms how important trust is as a mediator in the uptake of financial services powered by AI. While behavioral biases, subjective norms, financial awareness and innovativeness are significant antecedents, the role of trust should be emphasized in understanding how these affect intention to use. This study is an extension of previous theories of technology acceptance, such as TAM and the TTT, which have until now focused more on attitude or usefulness, and less on the intricate mediating role of trust (Bashir et al., 2025;Henseler et al., 2015). Financial awareness is an important antecedent that expands the theoretical lens, linking the adoption behaviours to knowledge and confidence. This is particularly pertinent in emerging economies where there is a wide range of digital literacy. Lastly, the fit indices and significant R2 values in the model validation indicate the robustness of integrating behavioral, cognitive, and social perspectives when they are applied to the study of emotions. This research subsidizes to the implementation theory by collectively revealing the multi-faceted processes by which trust can translate internal and external factors into behavioral intention.

Practical Implications

The study provides a number of useful understandings for experts and policymakers looking for to encourage robo-advisory adoption. Building trust through openness, strong data security, and hybrid advisory models should be the main goal of financial institutions. Financial awareness can also be enhanced through user education and user-friendly tools, thereby increasing user confidence.

Adoption can be normalized by addressing behavioral biases with tailored recommendations and nudges, as well as by utilizing peer pressure and testimonies. Promoting innovative features and trial usage may also increase acceptance. When combined, these tactics can hasten the adoption of robo-advisors in developing financial markets.

Conclusion

This study focused on the mediating function of trust while analyzing the variables affecting the uptake of robo-advisory services. The results showed that although behavioral biases, financial awareness, subjective norms, and innovativeness all have a substantial impact on adoption intention, trust plays a major role in how these effects are communicated. As a key construct, trust was strongly supported by structural model results, which explained 63% of its variance and almost 59% of the variance in intention to use. These discoveries, which build on earlier studies on the acceptance of financial technology, highlight the fact that trust is still the primary factor in the adoption of robo-advisors. The cross-sectional design and use of self-reported data, which could result in response bias, are limitations of this study. Future studies ought to use longitudinal designs, compare findings between nations, and include other factors which contribute the trust enhancing behaviour. Understanding of robo-advisory adoption could be further enhanced by investigating hybrid advisory models and developing trust-building techniques.

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