RESEARCH PAPER

Understanding Investor Adoption of Robo-Advisory Services: The Role of Regulatory Oversight and Behavioural Reasoning Using the BRT Mode

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AbstractThis research aims to understand the enablers and barriers to the adoption of automated wealth management services (robo-advisory) among Indian customers. The researchers used the framework of Behavioural Reasoning Theory (BRT) to understand the enablers and barriers to AI adoption, as well as the role of the regulatory framework in the adoption of robo-advisory. The data were collected through a structured questionnaire and a multi-stage sampling technique. At stage 1, the researchers used stratified sampling, and at stage 2, purposive sampling. The data was collected from all 4 metro regions and Bangalore to provide a representative sample of Indian Investors. The results of the study emphasised the role of service trust as a significant variable affecting AI-based investment. Other variables, such as perceived usefulness, perceived ease of use, and attitudes, were also found statistically significant. This study is an important contribution to the existing body of knowledge on technology adoption, as it significantly explains (R^2 = 84%) the factors affecting robo-advisory adoption in investment services. The study also suggests important clues for service-providing companies to frame their business strategy in such a way that they can attract maximum clients and achieve a competitive advantage

Keywords: Artificial intelligence, BRT Theory, Robo advisory, Wealth management, Technology adoption
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1. Introduction The rise of financial technology has reshaped the investment world. Robo-advisors now play a growing role in this shift. These AI-powered platforms offer low-cost, data-driven advice with minimal human contact (Sironi, 2016). They use client inputs—like income, age, and goals—to build and manage portfolios. -Advisors reduce entry barriers. Small investors can now access tools once limited to high-net-worth individuals. Many platforms charge lower fees than traditional advisors, making them more appealing to younger or cost-conscious users (Senteio, 2024). Easy-to-use apps, round-the-clock access, and quick onboarding also drive adoption. These systems follow clear algorithms. When market conditions shift, portfolios rebalance automatically. Real-time data drives updates, helping users stay aligned with their goals (Hodge et al., 2021). Automation reduces delays and helps remove emotional responses from decision-making. The 2008 financial crisis pushed many investors to seek alternatives. Robo-advisors filled that demand with low-fee, self-directed investment options. Early platforms like Betterment and Wealthfront attracted tech-savvy users who valued transparency and control (Flavián et al., 2022). One major strength of robo-advisors is their ability to reduce behavioural bias. Traditional investors often fall into patterns of overconfidence, panic selling, or trend-following. Automated platforms follow rules instead of emotion, offering consistent, data-backed suggestions (D'Acunto et al., 2020; Rossi et al., 2020). Studies link robo-advisory use to improved diversification and better risk-return profiles. Still, some key gaps remain. These tools may not fully understand an investor's personal needs or context. Most use simple risk questionnaires, which don't always reflect true comfort levels with market losses or volatility (Waliszewski & Zięba-Szklarska, 2020). Results can feel generic or rigid. Trust is another concern. Many users are hesitant to rely on non-human advisors, especially during periods of market instability. The lack of human judgment in high-stakes situations raises doubt (Oehler et al., 2024). Security concerns, data use policies, and limited transparency also affect acceptance. Young often prefers tech-first tools, but they still value trust and control. Their choices can influence how financial advice evolves. A clear view of their reasoning can guide product design and policy changes. Hybrid models may offer a path forward. These combine the precision of automation with human support. Investors could benefit from both data-driven logic and tailored guidance. This may also ease concerns about trust and emotional support. AI-based systems can reduce bias but may also carry hidden flaws. If the data used to train algorithms is biased, the system may reproduce that bias (Baker & Dellaert, 2019). That creates new risks, especially when the system lacks clear oversight. Improving these platforms calls for regular evaluation. It's not just about speed or low fees—ethical concerns, accuracy, and user trust matter too. As AI becomes more common in finance, these issues will shape how much—and how well—people use robo-advisory services. This study

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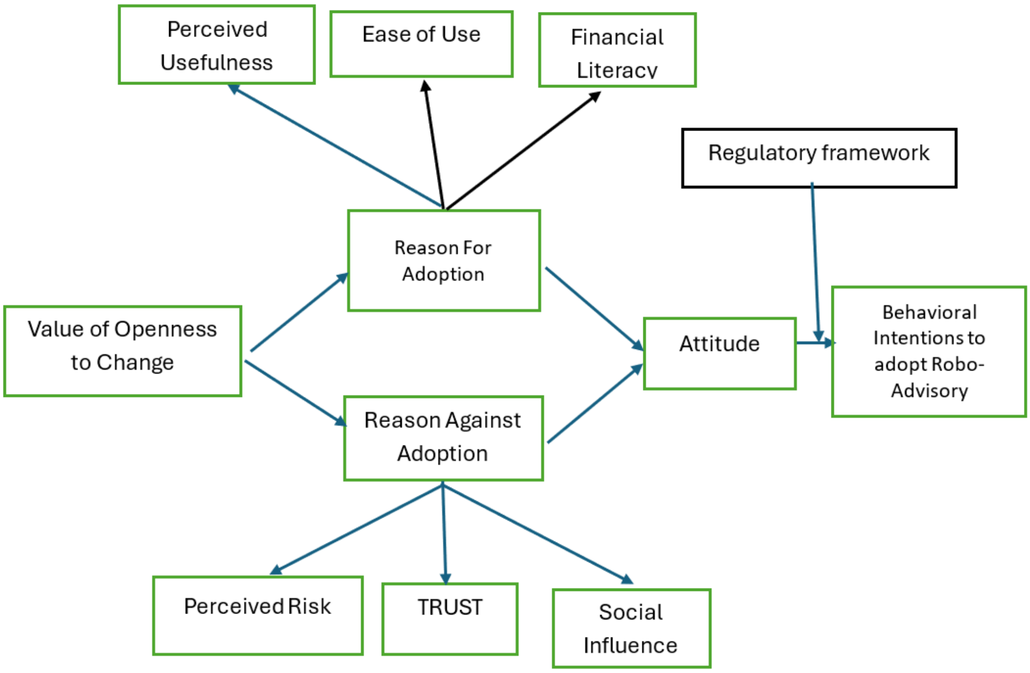
applies Behavioural Reasoning Theory (BRT) to explore the adoption of robo-advisors. BRT helps explain how people justify their choices and how beliefs shape action. The goal is to understand what drives or limits adoption, especially among digital-native investors.

2. Literature Review

Artificial intelligence (AI) has transformed how investors access and manage financial advice. Robo-advisors use algorithms to build, manage, and adjust investment portfolios with little to no human input. These tools aim to improve access, lower costs, and remove emotional decision-making from investing. Yet, despite their benefits, concerns about bias, fairness, and transparency remain (Kofman, 2024). One core concern is the risk of algorithmic bias. AI systems rely on historical data to predict future outcomes. If past data reflect inequality or flawed assumptions, the model can reproduce those issues. This may result in certain investor groups receiving poorer recommendations, widening financial gaps rather than closing them (Singh & Kumar, 2024). For instance, investors with lower income or limited financial knowledge may receive more conservative portfolios, which could limit long-term returns. Addressing this requires bias checks, regular audits, and strong data governance. Behavioural finance studies show that human investors often make irrational decisions. Biases such as overconfidence, loss aversion, and inertia can lead to poor outcomes (Thaler & Sunstein, 2008). Robo-advisors are promoted as a way to correct this. By removing emotion, they can recommend disciplined strategies based on risk tolerance and long-term goals. However, AI is not immune to bias. If models are trained on flawed or narrow datasets, they can reinforce investor mistakes rather than fix them (Kiani & Shafiee, 2022). Another key challenge is transparency. Many robo-advisors operate as "black boxes," offering little insight into how decisions are made. Investors may receive advice without understanding how or why certain choices were recommended (Aldemir & Uçma Uysal, 2025). This lack of clarity can erode trust, especially during times of market stress when users may want to understand shifts in portfolio allocation. Explainable AI (XAI) is emerging as a solution. It allows investors and regulators to understand how decisions are made and whether they align with user goals. The literature stresses the importance of clear interfaces, plain-language disclosures, and simplified reporting tools to enhance investor understanding (Chambers & Partners, 2024). Global regulation of AI in finance is still evolving. The European Union's AI Act takes a broad, risk-based approach, while the U.S. favours a more sector-specific strategy. This mismatch creates friction for firms operating in multiple markets, forcing them to navigate complex, conflicting rules (Daiya, 2024). There is growing support for a unified global framework. This would streamline compliance, reduce costs, and ensure consistent investor protection worldwide. Regulatory alignment also helps maintain market integrity and promotes fair access to robo-advisory services across borders. Ethical AI is another growing area of concern. Fairness in financial advice goes beyond technical accuracy. It involves protecting investors from biased, misleading, or one-size-fits-all strategies. Ethical frameworks should include regular bias audits, transparency in algorithm design, and investor education initiatives. Educating users helps them understand the advice they receive and allows them to ask better questions or seek second opinions when needed (Kumar et al., 2024). Investor trust is central to the success of robo-advisors. Research shows that users are more likely to adopt these tools if they understand how they work and feel confident in their fairness (Oehler et al., 2024). Factors like control, risk perception, and emotional comfort play a major role. Tools that blend automation with limited human support—often called hybrid models—may offer a more balanced path. These systems provide the efficiency of AI with the reassurance of expert oversight. Robo-advisors hold great promise for making investing smarter and more inclusive. But to deliver on this promise, they must be transparent, fair, and free from bias. Regulatory efforts must evolve with the technology, and ethical safeguards must be built into every stage of development. Furthermore, this study addresses the gap by integrating **Behavioural Reasoning Theory (BRT)** with constructs such as financial literacy, emotional intelligence, data privacy concerns, and regulatory perceptions to build a more comprehensive, context-specific understanding of robo-advisor adoption. By doing so, it responds to the pressing need for models that bridge **technological innovation with human reasoning, social validation, and policy relevance** in the digital investment space. Future research should explore better ways to explain AI decisions, reduce embedded bias, and test how different users respond to robo-advice. Only by addressing these challenges can we ensure AI serves all investors fairly.

3. Conceptual Framework and Hypothesis Development

This study employs **Behavioural Reasoning Theory (BRT)** to explore behavioural and structural influences on robo-advisor adoption among investors. BRT emphasises that individual behaviour is shaped by both reasons for and against a decision, offering deeper insights than linear models such as the Theory of Planned Behaviour (Ztaby, 2005). It considers underlying beliefs and values, which drive the reasoning process and shape behavioural intentions. In the context of robo-advisory services, BRT helps explain why some investors adopt automated investment platforms, while others resist them, despite clear



(Source: Author's own work) (Fig: 1)

3.1 Openness to change

Openness to change significantly influences an investor's behavioural inclination to use robo-advisors by promoting flexibility and reducing mental resistance to financial automation. Brown and Jones (2021) note that investors who are more open to change are more prone to see robo-advisors as effective, clear, and useful for investment management. This flexibility reduces behavioural biases such as inertia, loss aversion, and scepticism towards technology that often slow fintech adoption (Köhler et al., 2022). Acceptance of change also increases perceived utility and ease of use, two of the primary elements of the Technology Acceptance Model (TAM), further boosting confidence in digital financial products (Smith et al., 2023). Openness to change is a major driver of adoption by fostering a positive attitude towards robo-advisory services, therefore making it a key factor for financial businesses and fintech companies expanding automated wealth management solutions. According to peer recommendations and market developments (Lee and Patel, 2024), young investors are more likely to embrace fintech solutions. This also enhances social influence. Thus, it is supposed that Openness to change positively influences investors' behavioural intention to use robo-advisors.

H1: Openness to change positively influences the behavioural intention of investors to use robo-advisors.

3.2 REASON FOR

3.2.1 Financial literacy

Financial literacy is an important factor influencing investors' acceptance of robo-advisors. Bessa (2024) contends that financial literacy increases people's capacity to evaluate investment risks accurately, make sound decisions, and understand complex financial instruments. Knowledgeable investors can more effectively assess the advantages and drawbacks of AI-driven financial services, so higher financial literacy is associated with greater trust in these services. Financial literacy also reduces dependency on conventional human advisors by giving people more confidence to make their own financial decisions (Qadoos et al. 2024). Consequently, financially literate people would likely see robo-advisors as a reasonable means for managing their investments.

H2 (H2a): Consumers' will to engage robo-advisors is positively affected by financial literacy.

3.2.2 Perceived Usefulness

A main predictor of technology adoption, perceived usefulness is a core component of the Technology Acceptance Model (TAM). Roh et al. (2023) contend that users will likely embrace artificial intelligence-driven financial tools if they value their speed, precision, and ability to maximise investment returns. According to the Unified Theory of Acceptance and Use of Technology (UTAUT), their study shows that performance expectancy—closely linked to perceived usefulness—positively affects attitudes toward robo-advisors. Still, worries about privacy, trust, and security can dampen this link, therefore restricting use even in light of apparent advantages (Kwon et al., 2022). Still, investors who appreciate robo-advisors will likely embrace them more often, since they provide real-time financial intelligence and data-driven advice.

H2b: Consumers' intention to embrace robo-advisors rises with perceived usefulness.

3.2.3 Ease of Use

Particularly in digital financial services, the ease of use of a technology greatly affects its acceptance. According to Belanche et al. (2019), a user-friendly interface, easy navigation, and clear investment advice improve consumers' desire to use robo-advisors. Effort expectancy, which is closely related to the ease-of-use construct in UTAUT, is crucial in determining whether people feel comfortable using AI-driven financial systems. Furthermore, contributing to a good user experience and, hence, increasing adoption are simplified onboarding procedures, interactive dashboards, and responsive customer service (Yeh et al., 2023). The study shows that if users see them as simple to use and requiring little effort, robo-advisors are more likely to be accepted by those with minimal technological knowledge or financial acumen.

H2c (H2c): Intended use positively the customer's intention to use computer advice by means of consumer thinking.

3.3 Reasons against

3.3.1 Privacy risk

Privacy risk refers to the potential adverse effects consumers might suffer from unauthorised use, misuse, or exposure of their personal financial data. Data breaches, hacking incidents, and opaque data management practices contribute to privacy concerns in robo-advisors. Consumers tend to be afraid of identity theft and financial losses, which stops them from using automatic systems for investment decisions. Higher perceived privacy risks lower consumers' openness to using financial technology solutions (Belanche et al., 2025). According to Cheng et al. (2019), those who view financial technology services as high-risk are much less likely to accept them. Any perceived weakness in data security undermines consumer trust in robo-advisors, as personal financial information is vital to their operations. Therefore, privacy risk depresses the desire to use robo-advisors.

H3a (H3): Consumers' desire to embrace robo-advisors will decline due to privacy threats.

3.3.2 Trust

Especially in financial services, trust in robo-advisors encompasses confidence in their ethical behaviour, security, and dependability—and is therefore a key driver of technology use (Scherer & Lehner, 2023). Concerns over algorithmic decision-making, potential biases, and the inability to offer personalised guidance as close to that of human advisors all contribute to a lack of confidence in robo-advisors (Cheng et al., 2019). Consumers sometimes have difficulty believing in the accuracy and equity of algorithm-driven financial products, therefore impeding their acceptance. Trust transfer theory suggests that institutional trust and supervisory control mechanisms can benefit trust in robo-advisors (Nourallah et al., 2022). On the other hand, in the absence of regulatory oversight, openness, and consumer education, doubts prevail about the dependability of robo-advisors. Consumer confidence is further eroded by negative perceptions of algorithmic errors, unanticipated market swings, and possible ethical problems. Regulatory systems, third-party audits, and strong customer service policies can facilitate trust and motivate adoption. Unless these trust-boosting elements become widespread, trust concerns will keep consumer acceptance of robo-advisors low. Earning consumers' permission to use robo-advisors will be somewhat hindered by trust issues.

H3 (H3b): Trust issues will negatively affect consumers' intention to adopt robo-advisors.

3.3.3 Social Influence

Particularly for cutting-edge financial products, social influence is vital in shaping consumer behaviour. Subjective norms, defined as the perceived social pressure to adopt or reject a technology, significantly influence technology acceptance (Belanche et al., 2025). Individuals are more likely to adopt robo-advisors if they receive positive endorsements from peers, financial experts, or media sources. Conversely, negative social influence, such as scepticism from trusted sources or adverse media coverage, deters adoption. Studies highlight that individuals with low familiarity with AI-driven financial services are more susceptible to social influence (Nguyen et al., 2023). If influential figures, such as financial advisors or institutional investors, express doubts about the effectiveness of robo-advisors, potential users may refrain from adopting them. Moreover, resistance results from societal expectations about confidence in human financial consultants versus automated solutions. Thus, negative social influence would serve as a barrier inhibiting customers from embracing robo-advisors.

H3 (H3c): Consumers' motivation to adopt a robo-advisor will be against social influence.

3.4 Behavioural Intention to Adopt

As finance turns more digital, robo-advisors are gaining traction. A key factor driving their adoption is investor attitude. Ajzen (1991) found that attitude strongly predicts behavioural intent. When investors see robo-advisors as useful and trustworthy, they are more likely to use them. The Technology Acceptance Model (Davis, 1989) links this attitude to two drivers: ease of use and perceived usefulness. Robo-advisors provide constant access, algorithm-based advice, and less human bias features that build user confidence.

Trust is another core element. Investors value transparency, consistent performance, and secure data handling. These traits shape the trust and support that drive intent to adopt (Baker & Dellaert, 2017). Cost also matters. Compared to traditional advisors, robo-advisors charge lower fees. This appeals to tech-savvy users who value affordability (Ji, 2017).

Social cues also influence adoption. When peers use robo-advisors or leave positive reviews, others take notice (Venkatesh et al., 2003). Yet, some investors resist automation due to overconfidence in their skills. Still, when shown strong algorithmic results and back-

tested data, they become more open. Thus, it is hypothesised that a positive attitude toward robo-advisors significantly increases an investor's intention to adopt them.
H4: A Positive Attitude Towards Robo-Advisors Significantly Increases a consumer's Behavioural Intention to Adopt Them

3.5 Regulatory Framework
Robo-advisors are reshaping investment services by offering automated advice to a broad range of users. A clear and supportive regulatory framework plays a key role in building investor trust, reducing risk, and encouraging adoption. Strong policies ensure transparency, accountability, and user protection. Consistent oversight helps limit system-wide risks, reduce algorithmic errors, and support financial stability (Financial Stability Board, 2017).
Openness in how algorithms make decisions and how data is handled also matters. When investors understand how their data is protected, they feel more secure, which can increase their intent to adopt (Reserve Bank of India, n.d.). RegTech—technology used by regulators—adds further value. It helps monitor risk, improve compliance, and support digital innovation without heavy restrictions (Arner et al., 2017).
Still, too much regulation can slow progress. A balanced, flexible approach is needed (OECD, 2017). Overall, a well-designed regulatory system makes investors more likely to accept robo-advice.
H5: A favourable regulatory framework positively affects investors' behavioural intention to use robo-advisors.

4. Methodology
4.1 Survey instrument
A structured questionnaire was used to collect primary data from respondents. The questionnaire consisted of 30 items designed to measure 10 latent constructs of the research model: Openness to Change (VOC), Financial Literacy (FL), Perceived Usefulness (PU), Ease of Use (EOU), Perceived Risk (PR), Trust (TT), Social Influence (SI), Attitude (ATT), Regulatory Framework (RGF), (BI) behavioral intention to accept the use of robo-advisors. All measurement items were adapted from previous studies to ensure reliability and validity. Specifically, items for each construct were sourced from relevant literature. Each item was measured using a 5-point Likert scale, where 1 represented "strongly disagree" and 5 represented "strongly agree." Additionally, the questionnaire included demographic questions to capture respondents' characteristics, such as age, gender (1 = male, 2 = female), and prior experience with robo-advisors (1 = yes, 0 = no).

4.2 Sample and Data Collection
The participants in this study were young individuals in India's metropolitan cities who invested in the stock market. Young investors were defined as those aged 18 to 29. A purposive sampling technique was used to select the target respondents. Data was collected through both offline and online methods. Hard copies of the questionnaire were distributed to young investors at events such as seminars, workshops, and training programs organized by stockbroker houses and investment education providers, a method employed in prior studies (Chong et al., 2021). Additionally, online surveys were sent to students and alumni of the Executive MBA (EMBA) program at a leading business school in India. Since EMBA students typically had at least 2 years of work experience and demonstrated financial capability, they were considered relevant to this study. Shown in Table 1.

City	Number of samples
Delhi	100
Mumbai	100
Bangalore	100
Chennai	100
Pune	100
Hyderabad	100

Table 1. Sample Size

4.3 Assessment of Normality
The skewness-Kurtosis methodology was used to test the normality (univariate) of the variables (Hair et al., 2010; Byrne, 2010). All these values were computed using SPSS-17 (a software package for the social sciences). All computed values were within their recommended ranges. As reported in Table 2, the value of skewness was found below the threshold value of 3, and that of kurtosis was found below the threshold value of 8 (West et al., 1995; Kline, 2011).

	Mean	Std. Deviation	Skewness	Kurtosis

VOC1	3.835	.8677	.264	-.053
VOC2	3.754	.8667	.296	.103
VOC3	3.756	.8642	.493	.388
FL1	3.987	.7678	-.490	.239
FL2	3.998	.7957	-.496	.447
FL3	3.985	.7773	-.489	.368
PU1	4.004	.8482	.470	.487
PU2	3.896	.8347	.314	.299
PU3	4.033	.7927	.376	-.088
EOU1	3.792	.8552	.519	.147
EOU2	3.722	.8904	.268	.044
EOU3	3.676	.8585	.327	.106
PR1	3.692	.9568	-.288	.025
PR2	3.578	.9026	-.208	-.097
PR3	3.603	.9103	-.445	.099
TT1	3.298	1.1472	.452	.095
TT2	3.353	1.1178	.328	-.368
TT3	3.658	1.1213	.325	-.136
SI1	3.484	.9335	-.546	.387
SI2	3.487	.9103	-.424	.115
SI3	3.734	.8825	-.386	.137
ATT1	3.626	.8718	.424	.059
ATT2	3.688	.8704	-.499	.146
ATT3	3.658	.8466	.548	.288
RGF1	3.838	.8697	.265	-.063
RGF2	3.750	.8687	.297	.113
RGF3	3.751	.8662	.564	.398
BI1	3.982	.7688	-.533	.249
BI2	3.990	.7977	-.494	.457
BI3	3.988	.7763	-.488	.378

Table 2: Assessment of Normality

(Source: Author's own work)

Financial Literacy (0.767–0.795) and Behavioural Intention (0.768–0.797) had low standard deviations, indicating consistency among participants. Openness to Change, Perceived Usefulness, Ease of Use, Perceived

Risk, Social Influence, Attitude, and Regulatory Framework have moderate standard deviations (0.80–1.0), indicating that participants had varied responses. Trust has the highest standard deviation (1.117–1.147), indicating that participants held different views on trust in robo-advisory services. Even with these differences, all standard deviations are within the limits, so the data is reliable. Based on the skewness, kurtosis, and standard deviation results, the data appear to be normally distributed. So it's good to go for parametric tests like t-tests, ANOVA, regression, and SEM. Since all constructs are within normal range, no data transformation is needed.

4.4 Standardised loadings, Cronbach's alpha values, CR, and AVE

Confirmatory factor analysis (CFA) was conducted to assess the reliability and validity of the collected data, and the maximum likelihood method was used to estimate the model parameters in the present study. All analyses were conducted on variance-covariance matrices (Hair et al., 2010). The standardised loadings, Cronbach's alpha, average variance extracted (AVE), and composite reliability (CR) were used to assess the convergent and discriminant validity of the measurement model shown in Table 3

Constructs	Items	Standardized loadings	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Openness to Change (VOC)	VOC1	0.789	0.838	0.84	0.633
	VOC2	0.768			
	VOC3	0.829			
Financial Literacy (FL)	FL1	0.897	0.904	0.908	0.771
	FL2	0.893			
	FL3	0.844			
Perceived Usefulness (PU)	PU1	0.824	0.863	0.89	0.696
	PU2	0.825			
	PU3	0.854			
Ease of Use (EOU)	EOU1	0.868	0.846	0.88	0.673
	EOU2	0.807			
	EOU3	0.785			
Perceived Risk (PR)	PR1	0.799	0.826	0.865	0.636
	PR2	0.806			
	PR3	0.787			
Trust (TT)	TT1	0.786	0.899	0.992	0.606
	TT2	0.761			
	TT3	0.788			
Social Influence (SI)	SI1	0.813	0.878	0.894	0.692
	SI2	0.834			
	SI3	0.848			
Attitude (ATT)	ATT1	0.820	0.845	0.897	0.633
	ATT2	0.799			
	ATT3	0.767			
Regulatory Framework (RGF)	RGF1	0.785	0.839	0.876	0.626
	RGF2	0.764			
	RGF3	0.824			
Behavioral Intention (BI)	BI1	0.893	0.894	0.793	0.766
	BI2	0.882			
	BI3	0.849			

Table 3: Standardised loadings, Cronbach's alpha values, CR, and AVE

(Source: Author's own work)

The study checked the measurement model for reliability and validity. It used standard tools—factor loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). These help confirm if the model works as expected. All factor loadings were above 0.70. They ranged from 0.761 to 0.897. Items for Financial Literacy and Behavioural Intention scored the highest. This shows strong links between the items and their constructs. Cronbach's Alpha showed high internal consistency. All scores were above 0.70. Perceived Risk scored 0.826. Trust scored 0.899.CR scores also showed strong reliability. They ranged from 0.793 to 0.992. AVE scores were all above 0.50. This means each construct captured enough of what it should. Overall, the model is good. It is both reliable and valid. The constructs measure what they are meant to.

4.5 Discriminant Validity

	VOC	FL	PU	EOU	PR	TT	SI	ATT	RF	BI
VOC	0.795									
FL	0.478***	0.876								
PU	0.497***	0.434***	0.842							
EOU	0.566***	0.369***	0.587***	0.827						
PR	0.468***	0.438***	0.641***	0.632***	0.768					
TT	0.635***	0.247***	0.459***	0.550***	0.343***	0.847				
SI	0.332***	0.359***	0.536***	0.439***	0.564***	0.434***	0.785			
ATT	0.453***	0.379***	0.588***	0.417***	0.592***	0.467***	0.518***	0.787		
RGF	0.575***	0.442***	0.633***	0.523***	0.665***	0.415***	0.517***	0.685***	0.735	
BI	0.289***	0.426***	0.586***	0.518***	0.557***	0.318***	0.537***	0.691***	0.589***	0.796

Note: Factor Correlation Matrix with squared roots of AVE on the diagonal
Table 3: Discriminant Validity
(Source: Author's own work)

The Fornell-Larcker test shows strong discriminant validity. Each construct links more with its own items than with others. The square root of AVE is higher than any cross-construct correlations. AVE scores range from 0.735 (Regulatory Framework) to 0.876 (Financial Literacy). This means each construct explains a good share of its own items.
Correlation results show how the constructs connect. Openness to Change is strongly linked to Trust (0.635) and Regulatory Framework (0.575). People open to change tend to trust robo-advisors more. They also see rules and laws as important. Perceived Usefulness and Ease of Use are also strongly correlated (r = 0.587). This fits with the TAM model. Easy tools feel more useful.
Perceived Risk has key links with Attitude (0.592) and Regulatory Framework (0.665). Rules help reduce fear, which shapes how people feel about robo-advisors. The biggest link for Behavioural Intention is with Attitude (0.691). A better attitude leads to a stronger intent to use. Social Influence also matters. It shows up in links with Behavioural Intention (0.537) and Perceived Risk (0.564). Friends, peers, and public views can shift how safe a tool feels. These links show the model works well. Discriminant validity is strong.

4.6 Measurement Model
All important and recommended fit indices were tested to assess model fit, as suggested by Hair et al. (2010) and Kline (2010). Since two important indices, i.e., GFA and CFAI, did not meet the threshold values, purifications and reassessments were conducted to ensure a good fit between the data and the proposed model. (Anderson and Gerbing, 1988; Bagozzi and Yi, 1988; Byrne, 2010). This is an iterative process that follows various criteria to enhance model fit, including the assessment of standardised regression weights (factor loadings), modification indices, and the standardised covariance matrix (Byrne, 2010; Hair et al., 2010). Table 5 below indicates the measurement values. All values obtained are within the threshold limits, indicating good model fitness.

Fit Index	Recommended Value	Measurement model value
X^2	NS at $p<0.05$	958.534

Df	N/A	570
X^2/df	<5	2.280
Goodness of Fit Index (GFI)	>0.90	0.921
Adjusted Goodness of Fit Index (AGFI)	>0.80	0.879
Comparative Fit Index (CFI)	>0.90	0.953
Normed Fit Index (NFI)	>0.90	0.928
Root Mean Square Residual (RMR)	<0.10	0.033
Root Mean Square Error of Approximation (RMSEA)	<0.08	0.047

Table 4: Results of Measurement Model

(Source: Author's own work)

The model fit is within acceptable limits. The chi-square value is 958.534 with 570 degrees of freedom. The test is significant ($p < 0.05$), which is expected given the large sample size. The chi-square/df ratio is 2.280, which is below the cutoff of 5. This suggests a good overall fit. Key absolute fit indices support the model. The Goodness-of-Fit Index (GFI) is 0.921, which is above the 0.90 threshold. This means the model explains a good share of the variance. The Adjusted Goodness of Fit Index (AGFI) is 0.879. Though slightly under 0.90, it's still within a fair range. The Root Mean Square Residual (RMR) is 0.033. This is well below the 0.10 limit, showing low error. The Root Mean Square Error of Approximation (RMSEA) is 0.047. It's under the 0.08 threshold, which signals a close fit.

Incremental fit indices also look strong. The Comparative Fit Index (CFI) is 0.953, and the Normed Fit Index (NFI) is 0.928. Both are above 0.90. This shows that the model performs well compared to a baseline model. Together, these numbers confirm that the model fits the data well. The results show a strong setup for testing the structural model using SEM.

4.7 Path Coefficients

The path results (Table 5) provide key insights into how the model constructs are connected. Openness to Change strongly affects both Reason For ($\beta = 0.520$, CR = 12.799, $p < 0.001$) and Reason Against ($\beta = 0.519$, CR = 16.865, $p < 0.001$). This means people open to change can see both the benefits and the risks of using robo-advisors. Reason For has a strong effect on Attitude ($\beta = 0.464$, CR = 7.885, $p < 0.001$). Positive drivers, such as good rules and clear systems, shape people's feelings about the tool. But Reason Against also matters. It strongly influences Attitude ($\beta = 0.389$, CR = 10.848, $p < 0.001$). Risk and doubt clearly affect how people view robo-advisors. Attitude, in turn, predicts both Regulatory Framework ($\beta = 0.297$, CR = 5.629, $p < 0.001$) and Behavioural Intention ($\beta = 0.512$, CR = 9.188, $p < 0.001$). This shows that a more positive attitude leads to greater trust in rules and a higher likelihood of adoption.

Second-Order Results

Reason for impacts: Financial Literacy ($\beta = 0.499$, CR = 10.738), Perceived Usefulness ($\beta = 0.349$, CR = 7.859), and Ease of Use ($\beta = 0.598$, CR = 11.586). Clear reasons in favour—like trust in systems or ease of use—help users feel more informed and in control. Reason Against drives Perceived Risk ($\beta = 0.497$, CR = 11.744), Trust ($\beta = 0.498$, CR = 10.639), and Social Influence ($\beta = 0.239$, CR = 7.895).Greater concerns raise fear, reduce trust, and affect how others shape user choices. All critical ratios exceed 7.8, confirming the strength of these links. These results support the model and show that both positive and negative beliefs shape attitudes, trust, and intention to adopt robo-advisors. Regulatory framework enhances investor confidence by establishing safeguards and clear standards for automated investment services. The findings corroborate earlier studies that emphasise the need for well-articulated policies to drive the mainstream acceptance of robo-advisors. Overall, this study illustrates the complex interplay between individual readiness, institutional trust, and social dynamics in facilitating technology adoption in the investment domain.

Path	Standardized total effect	Critical Ratio
RF<---VOC	0.520	12.799 ***
RA<---VOC	0.519	16.865***
ATT<---RF	0.464	7.885***
ATT<---RA	0.389	10.848***
RGF<---ATT	0.297	5.629***
BI<---ATT	0.512	9.188***
SECOND ORDER		
FL<---RF	0.499	10.738***

PU<---RF	0.349	7.859***
EOU<---RF	0.598	11.586***
PR<---RA	0.497	11.744***
TT<---RA	0.498	10.639***
SI<---RA	0.239	7.895***

Table 5: Path Analysis
(Source: Author's own work)
Notes: *p<0.001, **p<0.001, ***p<0.001

Moderating effect test

Variable	**Standardised β**	**t-Statistic**	**p-Value**
Step I: Main variables			
RGF	**0.6046**	**18.319**	**0.000**
ATT	**0.2465**	**6.5342**	**0.000**
Step II: Two-way interaction terms			
RGF × ATT	**0.0621**	**1.791**	**0.000**
ΔR²	**0.023**	**—**	**—**
ΔF	**4.213**	**—**	**—**
Dependent variable: BI			

Table 7: Results of moderating effect test with Regulatory Framework (RGF)
(Source: Author's own work)
Table 6: **Moderating effect test**

The moderating effect result (Table 6) shows that the regulatory framework and attitude significantly predict behavioural intention. The interaction between the regulatory framework and attitude improves the model, indicating a significant moderating effect.

5. Discussion

The findings reveal that young investors are increasingly curious about robo-advisors, but their willingness to adopt these tools often depends on how informed and confident they feel. Those with higher financial literacy are more likely to use algorithm-based platforms, as they're better equipped to assess the associated risks and functionality. This is in line with what prior studies have suggested—when investors understand financial tools, they're more likely to trust them. However, trust isn't built on knowledge alone. Many participants expressed doubts about data safety and a lack of clarity in how robo-advisors operate. The absence of clear communication about algorithmic logic and data protection often led to hesitation. Robo-advisory platforms must work to demystify their systems and make users feel secure, not just digitally but emotionally. Social influence also showed up as a strong factor. Many respondents admitted their decision to use or avoid robo-advisors was shaped by peer feedback—positive or negative. This suggests that beyond marketing and user interfaces, word-of-mouth and digital testimonials could play a bigger role than anticipated. Importantly, a clean and trustworthy regulatory environment adds another layer of confidence. When policies on data protection and AI ethics are visible and well communicated, adoption tends to improve. This supports earlier findings that policy frameworks are crucial for building investor trust in emerging technologies.

6. Theoretical Contributions

This research deepens understanding of robo-advisor adoption by moving beyond technical factors to explore behavioural, social, and institutional drivers. By combining financial literacy, trust, social dynamics, and regulatory influence, the study provides a well-rounded framework for understanding how young investors interact with fintech platforms. We observed that confidence in algorithms is not only built through usability but also through peer validation and perceived oversight. That adds a social and psychological dimension to what's often treated as a tech-only adoption issue. Additionally, incorporating a regulatory lens helps situate adoption within a real-world policy context—something many previous models omit.

Perhaps most notably, the proposed model moves beyond traditional frameworks such as TAM and UTAUT by integrating the Brt model with key factors. This gives researchers and practitioners a fuller view of what actually motivates or prevents adoption, especially among digitally native yet cautious investors.

7. Practical Implications

Financial institutions and policymakers have several takeaways here. First, investing in financial literacy programs can make a real difference. Our results show that better-informed users are more open to engaging with digital advisors and are more resilient to misconceptions. Second, concerns around transparency and data protection must be directly addressed. Robo-advisory firms should not just say they're secure—they need to show how, in plain terms. Adding explainable AI features and making algorithmic decision paths more visible could go a long way in building trust.

Behavioural tendencies like overconfidence, loss aversion, and inertia also shape usage patterns. Even though algorithms are designed to neutralise these biases, the user's own psychology still plays a role. Developers might consider interface designs and messaging that nudge users toward more rational decision-making. The regulatory aspect cannot be ignored. Clarity around consumer protection, AI ethics, and data privacy enhances credibility. Financial regulators could consider publishing plain-language summaries of robo-advisor guidelines to make the rules more approachable. Lastly, word-of-mouth is powerful. Positive reviews from credible voices—friends, influencers, or respected financial figures can significantly influence adoption. Financial firms should actively encourage user-generated testimonials and transparent feedback loops on digital platforms.

8. Limitations and Future Scope

While the study presents important findings, there are limitations. The sample was restricted to young investors in the metropolitan region, and although purposively chosen, it may not reflect broader demographics across India. Future research could benefit from a larger, more diverse sample to validate these insights across cities, income groups, and experience levels. Also, our focus on a select few behavioural biases leaves room for deeper exploration. Future work could examine additional cognitive and emotional patterns—like regret aversion or familiarity bias—that may affect how robo-advisors are perceived.

Since fintech is evolving rapidly, longitudinal studies would be valuable. Observing how trust, satisfaction, and usage behaviour change over time, especially with repeated exposure, could yield richer insights. Comparative studies between robo-advisors and traditional human advisors could also be illuminating, especially under volatile market conditions. Finally, investigating how changes in regulatory policy directly affect user sentiment and adoption behaviour could inform future policy frameworks.

9. Conclusion

This study offers a comprehensive look at the factors influencing robo-advisor adoption among young investors. By analysing a mix of behavioural, technological, and institutional variables—such as perceived usefulness, ease of use, openness to change, trust, financial literacy, perceived risk, and social influence—we provide both theoretical and real-world insights into digital investment behaviour. Our findings show that behavioural intention is shaped not just by usability but also by how well the platform earns the investor's trust and fits into their social and emotional decision-making processes. Financial literacy, supportive regulation, and peer influence are key enablers, while concerns about data privacy, lack of human interaction, and general scepticism toward AI remain notable obstacles. As robo-advisors continue to evolve, their success will depend not only on better algorithms but also on how well they connect with human psychology, social trust, and policy safeguards. Bridging this gap between automation and empathy will be critical to the future of digital financial advising.

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