Factors Influencing Investors' Adoption of Robo-Advisors in Bangalore: An Extrapolation from the Fiduciary Duty of Investment Advisors

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ABSTRACT

Robo-advisors are one of the prominent fintech innovations seen in the era of digitization. This study intended to investigate the factors that influence robo-advisor adoption among investors in Bangalore, India. It integrates the principles of Fiduciary Duty (Care and Loyalty) with the Technology Acceptance Model (TAM). From the analysis of 301 valid responses, the research found that while all fiduciary drivers are significant, Firm Reputation acts as the strongest predictor of value, and Privacy Protection is the primary driver of trust. Interestingly, investment experience did not moderate the relationship between trust and adoption, which suggests that there is a universal trust threshold across all investor segments in the Bangalore market.

Keywords: Robo-Advisors; FinTech Adoption; Fiduciary Duty; Technology Acceptance Model; Perceived Value; Trust; Privacy Protection; Firm Reputation.

INTRODUCTION

Digitization has essentially changed how financial services are provided and consumed in investment advisory scenarios. Robo-advisors, which are algorithmically based platforms that seek to automate the management process of a portfolio have been developed to be scalable and cost-effective to the traditional human advisor. These platforms are offered to bring increased efficiency, increased accessibility, and objective decision-making through the use of artificial intelligence and data analytics. Prior research has empirically shown that perceived usefulness and technological functionality have a substantial association with the adoption of fintech, especially in digitally active markets (Belanche, 2019; Nguyen, 2023). However, the digital products of investment advisory services are quite unlike others because they are provided in a fiduciary nature, which requires competence, transparency, and total dedication to the interests of a client.

Robo-advisory services are currently becoming common in the Indian fintech ecosystem and, more specifically, in the city of Bangalore, technological innovation, and retail investment activity center, but they have not been penetrated as intensively as in other global markets. Although, Indian investors are increasingly adopting digital financial services, adoption of fully automated advisory systems raises the perceived risk because of financial uncertainties and sensitivity of data. Investor decisions in such situations, just as in associations to technological qualities, are influenced by credibility perception, the image of an institution, and ethical accountability.

The current literature mainly explores the use of robo-advisors based on the technology acceptance model (TAM) and focuses on such constructs as perceived usefulness, ease of use, and social influence (Shiva, 2023; Senteio, 2024). Despite the usefulness of these models, they are more likely to weaken the ethical foundations that operate on a deeper level to affect the relationship between financial advisers and clients. Fiduciary duty (including responsibility of care (competence and performance) and loyalty (protecting privacy and managing conflicts of interest) is one of the basic but least researched predictors of trust in algorithmic systems by investors.

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Moreover, most of the existing researches have a global or cross-national orientation, thus excluding most emerging markets like India. The Bangalore scenario is quite relevant due to its technological advancement, government regulation through SEBI and growing retail involvement in the capital markets. However, little research has directly incorporated the constructs of fiduciary duties and value and trust perceptions to explain the adoption of robo-advisor in this particular area.

Though more recent research has paid growing attention to fintech trust and adoption, little has been done to examine how fintech signals of fiduciary-congruency like performance efficacy, personalization, privacy protection, and reputation of firms simultaneously work together and affect psychological mediators and behavioural intention. Moreover, moderating status of the investment experience is also a hypothetical concept but has not been researched in the Indian scenario.

In order to fill these gaps, this study explores how the concept of fiduciary care and fiduciary loyalty dimension affects the perception of value and trust and how they mediate the formation of adoption intention among investors in Bangalore. Combining the notion of fiduciary duty with the developed technology acceptance theory, the given research contributes to the knowledge on adopting the robo-advisor ethically-grounded and context-specific perspective.

LITERATURE REVIEW

Understanding Fiduciary Duty in Algorithmic Advisory

Fiduciary duty can be easily distinguished in the case of human investments advisory, where the issues of care, loyalty, competence and prioritisation of client interests are involved. Nonetheless, when it comes to the issue of robo-advisors, it is slightly more complex when it comes to the interpretation of fiduciary responsibility because algorithms lack human judgement, yet they still offer advisory services. The question that Ji (2017) raised was whether automated systems are sufficient to meet the fiduciary standards, especially the duty of care and management of conflicts of interests. According to scholars, the fiduciary responsibility in online advisory relationships should be operationalised in terms of performance transparency, risk disclosure, and safe data governance means.

The fiduciary duty is now being viewed more as a behavioural indicator with regard to how investors think about it, rather than as a regulatory mandate, in more recent literature in fintech. Instead of analyzing the technological efficiency of robot-advisors, investors can consider whether such services prove to be competent (care) and ethical (loyalty). This makes fiduciary duty a multidimensional construct that defines perceived value and trust of algorithmic systems.

Fiduciary Drivers and Perceived Value

Various studies have investigated the drivers of technology acceptance in the context of robo-advisory and in most cases the Technology Acceptance Model (TAM) has been used. The perceived usefulness and ease of use have always remained important predictors of adoption intent (Shiva, 2023; Belanche, 2019). Performance efficacy the assumption that robo-advisors will be better at financial performance than an individual is a generalization of perceived usefulness in financial situations.

One more driver that has been identified is personalisation. According to Kwon (2022), customisation and tailored portfolio recommendations managed to decrease resistance and increase perceived utility. Nonetheless, it can also be seen as a bare minimum, as opposed to a high differentiator in technologically mature markets.

Besides these, corporate reputation has also been found to affect the perceived value. As Cao (2025) has pointed out, the concept of brand credibility and institutional support plays a significant role in mitigating uncertainty in the decisions on fintech adoption. This means that the reputation can be viewed by the investors as a testament to competence, which will add value in a perceived economic terms, not just on the technical terms.

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Fiduciary Loyalty, Privacy, and Trust Formation

The trust is always listed as a key factor that determines the adoption of robo-advisor. In contrast to conventional advisory relationships, which include the development of trust based on interpersonal interaction, algorithmic systems have to build trust using structural and reputational means. In this process, the privacy protection is of critical importance. The financial advisory platforms handle personal and transactional information that is sensitive, thus posing a higher perceived risk. According to Bashir et al. (2025), the issue of data security is an important barrier to the adoption of fintech in emerging markets. Safe data management, regulation and clear governance policies are thus indicators of fiduciary loyalty. Good reputation among firms is also associated with higher trust. Well known brands decrease the uncertainty caused by reputational signalling especially in markets where regulation familiarity might be low. Empirical evidence, however, indicates that reputation is associated with higher trust, although privacy protection tends to show a stronger association with trust perceptions as there is increased sensitivity with regard to personal financial information.

Perceived Value, Trust, and Adoption Intention

The current adoption models propose that behavioural intention is influenced by both cognitive and affective assessment. The perceived value in robo-advisor situations is the economic factor of adoption justification, and trust is the level of confidence in system integrity. The works using TAM and UTAUT models also show that perceived usefulness and trust are major predictors of intention to use financial technologies (Nguyen, 2023; Senteio, 2024). Trust has often shown one of the highest effect sizes in the studies of fintech adoption, especially in high-risk financial settings.

Nonetheless, the number of studies incorporating fiduciary-based antecedents into this pathway is not that high. Although usability and risk perceptions have been studied previously, few studies have placed fiduciary duty as an upstream variable that affects perceived value and trust at once. In addition, there is also an inconclusive potential moderating effect of investment experience. According to some scholars, more experienced investors are more pegged on performance measures as compared to the novice investors who are more pegged on trust and security. Limited empirical support has been made to prove this logic of segmentation especially in Indian contexts.

Synthesis of Literature and Research Direction

Altogether, the literature suggests that technological performance, personalisation, trust mechanisms, and reputational signals are the factors that affect the adoption of robo-advisors. Nonetheless, there are still three areas of concern. To start with, existing research is mainly based on global or cross-national sample, and there is a lack of empirical data in India, especially in the city of Bangalore, which is a fintech hub. Second, fiduciary duty has seldom been applied to formulating measurable behavioural constructs to affect perceived value and trust, even though this aspect is highly discussed in regulatory literature. Third, the moderating effect of investment experience is still theorized but is not empirically researched in emerging markets. The proposed study will seal these gaps by using the concept of fiduciary care (performance efficacy, personalisation) and fiduciary loyalty (privacy protection, firm reputation) as a single framework that can be used to examine the effect that these two elements have on the perceived value, trust, and adoption intention among Bangalore investors. In such a way, the study expands the existing traditional technology acceptance frameworks by an ethically justified approach based on the fiduciary theory.

The conceptual framework reveals that there are four important independent variables based on the principles of fiduciary duty and the technology acceptance literature. These variables are divided into two heads of Fiduciary Care and Fiduciary Loyalty. Fiduciary Care is an indication that it is the duty of the advisor to make financially sound decisions that are in the best interest of the client. Under this dimension, Performance Efficacy is the perceived quality of the robo-advisor to produce better or competitive financial gains compared to the traditional methods of advisory. It encompasses the assessment of algorithmic competence and technical reliability of the investor. Personalisation is the ability of the platform to provide personalised recommendations on investment based on personal financial objectives, risk level, and time period. Personalised advisory outputs shall tend to

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increase the perceived utility because they will fit to the preferences of an individual. Fiduciary Loyalty represents the ethical considerations of the advisory platform. Privacy Protection is a guarantee of safe management and protection of personal and financial information against misuse. Since financial data is sensitive, data security serves as a fundamental trust-making indicator. Firm reputation is the business reputation, institutional reputation and perceived trustworthiness of the robo-advisor provider. Good brand equity and regulatory congruency can result as heuristic cues that decreases uncertainty and increases confidence. Collectively, the four drivers will determine the degree to which investors will assess the economic worth and integrity of the robo-advisory platforms.

Theoretical Integration: Fiduciary Duty Theory and TAM

This study draws on two theoretical traditions that have largely developed in parallel: fiduciary duty theory, which originates in financial regulation and describes the obligations of care and loyalty an advisor owes a client (Ji, 2017; Duffy & Parrish, 2021), and the Technology Acceptance Model (TAM), which explains technology adoption through the utilitarian constructs of perceived usefulness and perceived ease of use (Belanche et al., 2019; Nguyen et al., 2023). Applied on their own, each theory addresses only part of the robo-advisor adoption decision. TAM explains why investors adopt a system that appears useful and easy to use, but it is silent on the ethical and relational obligations that are central to financial advisory relationships. Fiduciary duty theory, conversely, specifies what a trustworthy advisor owes a client, but was not developed to explain technology adoption behaviour.

The integration proposed here treats fiduciary duty not as a separate, competing explanation but as the theoretical source of the belief constructs that precede TAM's outcome variables in this context. Specifically, Fiduciary Care (Performance Efficacy and Personalization) is positioned as the antecedent of Perceived Value, functioning analogously to TAM's perceived usefulness: it captures whether the platform is judged competent and beneficial. Fiduciary Loyalty (Privacy Protection and Firm Reputation) is positioned as the antecedent of Trust, a construct that extends TAM beyond its original utilitarian scope to capture the ethical and relational confidence that a fiduciary context demands. Perceived Value and Trust then jointly predict Adoption Intention, mirroring TAM's behavioural intention outcome while carrying forward the ethical content of the fiduciary constructs that produced them. In this way, fiduciary duty theory supplies the content of what is being evaluated (competence and integrity), while TAM supplies the structure of how those evaluations translate into adoption behaviour. The bootstrapped mediation results reported in Section 7.8.1, in which Perceived Value and Trust both partially mediate the paths from the fiduciary predictors to Adoption Intention, provide empirical support for this integrated structure rather than treating the two theoretical traditions as merely juxtaposed.

CONCEPTUAL FRAMEWORK

Independent Variables Influencing Perceived Value and Trust

The conceptual model identifies four key independent variables, which were based on the principles of fiduciary duty and technology acceptance literature. These variables are categorized into two general themes: Fiduciary Care and Fiduciary Loyalty.

Fiduciary Care is a way of showing the advisor that he or she must act in the best financial interest of the client and competently. In this construct, the concept of Performance Efficacy refers to the perceived ability of the robo-advisor to produce better or competitive financial results relative to traditional advisory approaches, thus, it represents how investors evaluate the competence of algorithms and technical reliability. Personalization means that the platform is able to give investment advice based on the individual’s financial goals, risk tolerance, and investment horizon. It is assumed that personalized advisory outputs increase the perceived utility through the matching of recommendations to the personal preferences.

Fiduciary Loyalty represents the moral obligation that exists in the advisory platform. Privacy Protection refers to the guarantee that confidential and financial information is protected and safeguarded against abuse; since such data is sensitive in nature, data protection is a particular form of trust-building cue. Firm Reputation reflects

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the market reputation, institutional reputation and perceived trustworthiness of the provider of the robo-advisor. Existing brand equity and regulatory consistency reduce doubt and enhance confidence.

All these four drivers are expected to influence the assessment of economic worth and honesty of robo-advisory systems by investors.

Perceived Value and Trust as Core Psychological Mediators

The framework has Perceived Value and Trust as the center of the mediating constructs. Perceived Value is the judgment of the investor regarding the relevance of the benefits provided by the robo-advisor in relation to the costs, fees and risks, and is a cognitive assessment based on the performance expectations and cost-benefit considerations.

Trust is the confidence of the investor in the integrity, reliability, and moral things of the platform. In contrast to the old model of advisory relationship that is based on interpersonal interaction, performance signals, privacy protection and reputational clues create trust in the robo-advisor. According to the existing literature on the adoption of fintech, the identification of trust as a key psychological process that affects behavioral intention is consistent.

The framework has recognized that the attributes of fiduciary alignment cannot directly result in adoption but instead, these attributes influence internal assessments that in turn, guide decision-making by positioning perceived value and trust as mediators.

Adoption Intention as the Outcome Variable

Adoption Intention is formulated as the most important model outcome variable. It indicates the level of desire and the expected probability of using a robo-advisor in the future in terms of investment activities. The concept of behavioral intention has been traditionally a trusted source of actual usage behavior in technology acceptance literature.

In the financial advisory services sector, both economic rationality and perceived safety lead to the creation of adoption intention. The investors have to feel that there is enough value to make platform use worthwhile and at the same time trust the algorithmic system to be responsible and safe. In this regard, the model assumes the joint effect of perceived value and trust in the determination of the strength of adoption intention in investors.

Proposed Conceptual Model

According to the presented framework, the Fiduciary Care variables, such as Performance Efficacy and Personalization have a positive effect on Perceived Value, and Fiduciary Loyalty variables, such as Privacy Protection and Firm Reputation have a positive effect on Trust. In its turn, Perceived Value and Trust, in turn, improve Adoption Intention. The prospective moderating variable explored is Investment Experience that affects the relationship between Trust and Adoption Intention.

In this model, there is an ethically informed understanding of the adoption of fintech, as it highlights that technological efficiency is not the sole factor by which an investor makes his or her decision but also by competence and integrity, which are fiduciary-friendly indicators. The model provides a systematic account of the adoption behaviour of robo-advisors in Bangalore market by incorporating the performance-based and ethical drivers in a single framework.

Conceptual Model Diagram

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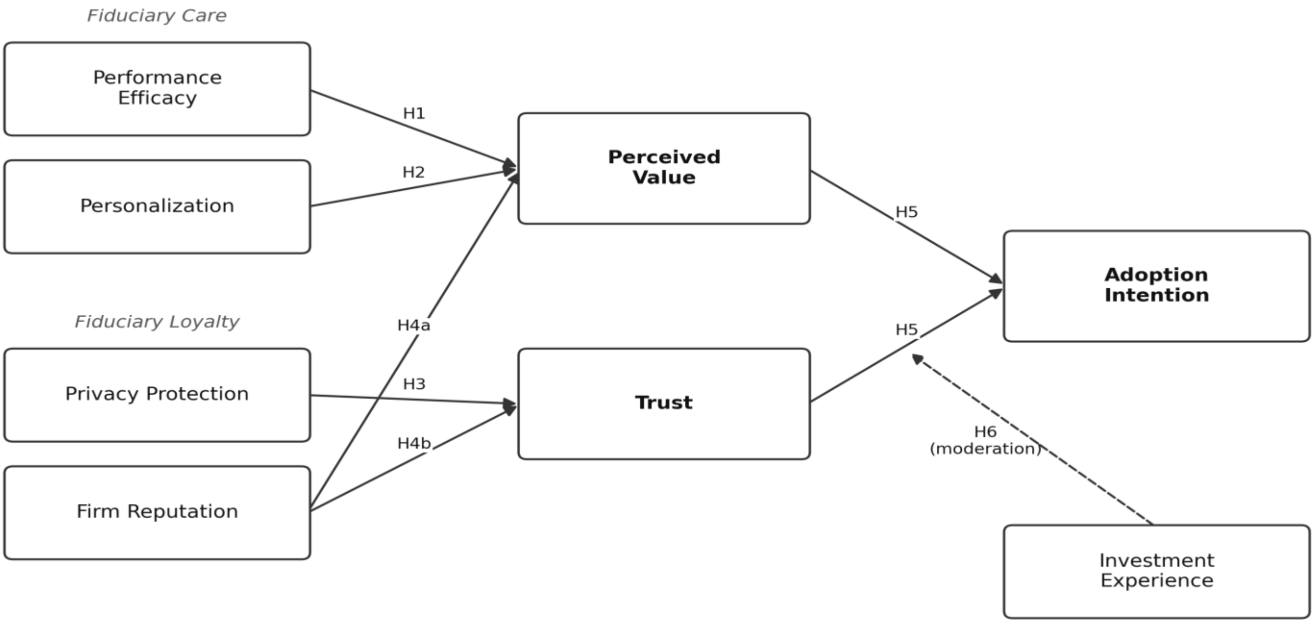

Figure 1. Proposed conceptual model of fiduciary-driven robo-advisor adoption

Hypothesis Development

Based on the conceptual framework and the extant literature, the following hypotheses are proposed:

- H1: Performance Efficacy (Fiduciary Care) positively influences Perceived Value.
- H2: Personalization (Duty to Inform) positively influences Perceived Value.
- H3: Privacy Protection (Fiduciary Loyalty) positively influences Trust.
- H4a: Firm Reputation positively influences Perceived Value.
- H4b: Firm Reputation positively influences Trust.
- H5a: Perceived Value positively influences Adoption Intention.
- H5b: Trust positively influences Adoption Intention.
- H6: Investment Experience moderates the effect of Trust on Adoption Intention.

RESEARCH METHODOLOGY

Research Design

The research used a quantitative, cross-sectional, and explanatory research design to establish the factors influencing adoption of robo-advisors among the investors who are based in Bangalore. The main aim was to test the role of fiduciary care and fiduciary loyalty on perceived value, trust and adoption intent. A structured questionnaire was used, which allowed statistical analysis of the relationships that were hypothesised. This explanatory framework was considered suitable because the research aimed at determining causal relationships between the antecedent variables, these include: performance efficacy, personalization, privacy protection and reputation of the firm and the outcome variables, perceived value, trust and adoption intention.

Data Collection

Primary data collection was carried out using a structured online questionnaire to potential retail investors in Bangalore using Google Forms. The questionnaire was in two parts:

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- **Section A:** Demographic and investment profile(age, investment experience, familiarity with robo-advisors).
- **Section B:** Measurement of constructs using five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

The variables were measured:

- Performance Efficacy
- Personalization
- Privacy Protection
- Firm Reputation
- Perceived Value
- Trust
- Adoption Intention

To support the theoretical framework and develop a hypothesis, secondary data were obtained using peer-reviewed journals, regulatory documents, and reports in the fintech industry.

Sampling and Sample Size

A non-probability sampling design that integrated convenience and snowball sampling methods was employed due to the logistical limitations, and because it was appropriate given the explanatory nature of the study. The target audience was retail investors in Bangalore who are familiar with robo advisors. A total of 302 responses were received at first, upon which the completeness check, and location filter were applied and 301 valid responses were statistically analyzed. The sample size is adequate for multiple regression analysis.

Tools for Analysis

The data were analyzed using Python (statsmodels library). The following statistical techniques were employed:

Test	Tool
Reliability Testing	Cronbach's Alpha
Descriptive Statistics	Mean & Standard Deviation
Correlation Analysis	Pearson Correlation
Multicollinearity Check	Variance Inflation Factor (VIF)
Impact Analysis	Multiple Linear Regression
Moderation Analysis	Interaction Term Regression

Reliability testing was used to assess the internal consistency of multi-item constructs. Correlation and VIF diagnostics were conducted before regression to ensure that there is no multicollinearity. Individual hypotheses were tested using Ordinary Least Squares (OLS) regression. Moderation was tested by using a mean-centered interaction term between Trust and Investment Experience.

Ethical Considerations

This study was conducted in accordance with the ethical guidelines applicable to survey-based academic research at RV Institute of Management, Bengaluru, and was cleared by the research supervisor prior to data collection.

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Participation in the survey was entirely voluntary, and respondents were informed of the purpose of the study, the voluntary nature of their participation, and the confidentiality of their responses before proceeding to the questionnaire. No personally identifiable information was collected, and all responses were used solely for the purposes of this academic study.

Data Analysis Framework

The analysis is aimed at explaining the impact of fiduciary-oriented drivers that include performance efficacy, personalization, privacy protection, and firm reputation on perceived value and trust and how these psychological mediators in turn affect adoption intention amongst the Bangalore investors. The design of its conceptual framework is to examine the direct as well as mediated relations in that order.

The quantitative analysis started with primary measures of diagnostics, such as reliability, descriptive statistics, and correlation analysis that assures consistency of measurements and construct validity. Before regression testing, multicollinearity test was carried out to ensure that the independent variables are independent within the model hence proving the statistical integrity of the data before hypothesis testing. The results were then used to analyse the effects of the fiduciary care variables (performance efficacy and personalisation) on perceived value; and fiduciary loyalty variables (privacy protection and firm reputation) on trust using regression analysis. The perceived value and trust were, subsequently, explored as predictors of adoption intention, which highlights the importance of these factors as the key psychological muscles in the decision-making process.

Moderation test was conducted to establish whether the influence of trust on adoption intention is affected by investment experience. The analysis included an interaction term to determine whether investor experience has an impact on the dependence on trust with regard to robo-advisor adoption. Instead of separating technological attributes, the analysis previews fiduciary duty as a behavioural construct based on which investors comprehend algorithmic competence and ethical correspondence. That systematic strategy makes it easy to understand the joint impact of economic assessment (perceived value) and ethical confidence (trust) in deciding to adopt a certain product in the Bangalore context in the fintech industry.

Data Analysis and Results

The findings derived from quantitative data collected from 301 valid respondents residing or working in Bangalore, are presented in this section. The data were analysed using Python (statsmodels), MS Excel, and statistical diagnostic procedures.

Reliability and Validity Analysis

Cronbach's Alpha was calculated to test the internal consistency of multi-item constructs.

Construct	Cronbach's Alpha	Interpretation
Fiduciary Care	0.748	Acceptable
Fiduciary Loyalty	0.885	Good
Adoption Intention	0.655	Acceptable

To assess whether Cronbach's Alpha alone was sufficient to establish construct validity, a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were conducted, followed by exploratory factor analysis (EFA) with varimax rotation on all ten measurement items. The KMO value was 0.853, well above the 0.60 minimum threshold, and Bartlett's test was significant ($\chi^2 = 1253.28$, $p < .001$), confirming the data were suitable for factor analysis.

Kaiser's criterion (eigenvalues greater than 1) indicated a two-factor solution, with the first two eigenvalues at 3.95 and 2.29 respectively. The rotated factor loadings are presented below.

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Table. Rotated exploratory factor analysis loadings (varimax)

Item	Factor 1	Factor 2	Communality
FC1 (Performance Efficacy)	0.04	0.72	0.52
FC2 (Personalization)	0.08	0.65	0.42
FC3	0.07	0.69	0.48
FL1 (Privacy Protection)	0.84	0.05	0.71
FL2 (Firm Reputation)	0.84	0.08	0.72
FL3	0.84	0.00	0.71
PV1 (Perceived Value)	0.53	0.40	0.44
TR1 (Trust)	0.49	0.44	0.44
AI1 (Adoption Intention)	0.53	0.38	0.42
AI2	0.54	0.40	0.45

The Fiduciary Care items (FC1–FC3) and Fiduciary Loyalty items (FL1–FL3) each loaded cleanly and distinctly onto their intended factor, supporting the validity of these two constructs. However, Perceived Value, Trust, and Adoption Intention did not emerge as separate factors and instead cross-loaded similarly across both factors. This is consistent with these three constructs being measured with only one or two items each, which limits the extent to which factor analysis can establish them as statistically distinct constructs.

Composite Reliability (CR) and Average Variance Extracted (AVE) were also computed for the multi-item constructs to complement the Cronbach's Alpha results reported above.

Table. Composite reliability and average variance extracted

Construct	CR	AVE
Fiduciary Care	0.748	0.498
Fiduciary Loyalty	0.885	0.719
Adoption Intention	0.654	0.486

Fiduciary Loyalty showed strong reliability and validity (CR = 0.885, AVE = 0.719). Fiduciary Care showed acceptable composite reliability (CR = 0.748), though its AVE (0.498) fell marginally below the conventional 0.50 threshold. Adoption Intention, measured with only two items, showed comparatively weaker reliability (CR = 0.654) and AVE (0.486). Taken together with the EFA results, these findings indicate that while Fiduciary Care and Fiduciary Loyalty are reasonably well-validated constructs, Perceived Value, Trust, and Adoption Intention are best interpreted as single/double-item proxy measures rather than fully validated multi-item constructs. This is acknowledged as a limitation of the measurement instrument in Section 11.

To assess the risk of common method bias arising from the use of a single self-administered questionnaire, Harman's single-factor test was conducted on all ten measurement items using unrotated principal axis factoring. The first (largest) factor accounted for 39.46% of the total variance, well below the 50% threshold conventionally used to flag common method bias as a serious concern (Podsakoff et al., 2003). This suggests that common method bias is unlikely to substantially affect the interpretation of the results reported in this study.

Descriptive Statistics

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The descriptive statistics reveal that Fiduciary Care (Mean = 3.96) is the only construct that reflects strong agreement among respondents. Other key variables, including Perceived Value (2.87), Trust (2.84), and Adoption Intention (2.86), fall slightly below the scale midpoint, which suggests that there is a neutral stance toward robo-advisors in the Bangalore market. Standard deviation values (0.58–0.93) indicate moderate agreement, while skewness and kurtosis levels are within acceptable ranges for further statistical testing.

Construct	N	Mean	SD	Min	Max	Skewness	Kurtosis
Fiduciary Care (Performance Efficacy)	301	3.96	0.58	2.67	5.00	-0.13	-0.61
Personalization	301	3.98	0.71	2.00	5.00	-0.14	-0.56
Privacy Protection	301	3.13	0.93	1.00	5.00	0.04	-0.25
Firm Reputation	301	3.15	0.90	1.00	5.00	-0.15	-0.25
Perceived Value	301	2.87	0.70	1.00	5.00	0.19	0.36
Trust	301	2.84	0.70	1.00	5.00	-0.13	0.48
Adoption Intention	301	2.86	0.60	1.50	5.00	0.25	0.18

Table. Descriptive statistics for study constructs (N = 301)

Demographic Profile of Respondents

Age Distribution

- 18–25 years: 57.81%
- 26–35 years: 22.26%
- 36–45 years: 10.63%
- 46+ years: 9.30%

The sample primarily represents young and middle-aged investors actively engaged in digital financial platform s.

Investment Experience

- Novice (Less than 2 years)- 56.15%
- Intermediate (2–5 years) – 24.92%
- Experienced (More than 5 years) – 18.94%

The distribution is dominated by novice investors; while intermediate and experienced investors are also represented.

Familiarity with Robo-Advisors

All of the 301 valid responders expressed familiarity with platforms such as Zerodha Coin, Kuvera, INDmoney, and Scripbox, confirming awareness within the sample.

Regression Analysis – Model 1

Dependent Variable: Perceived Value

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Independent Variable: Fiduciary Care

- $R^2 = 0.071$
- Model significance: $p < 0.001$
- Coefficient (Fiduciary Care) = 0.326

Fiduciary Care significantly influences Perceived Value, explaining 7.1% of its variance. This suggests that perceptions of performance efficacy and usability enhance economic evaluation of robo-advisors.

Regression Analysis – Model 2

Dependent Variable: Perceived Value

Independent Variable: Personalization

- $R^2 = 0.035$
- $p = 0.001$
- Coefficient = 0.186

Personalization significantly influences Perceived Value but explains only 3.5% of variance, which shows that it is more of an expected feature than a strong differentiator.

Regression Analysis – Model 3

Dependent Variable: Trust

Independent Variable: Privacy Protection

- $R^2 = 0.161$
- $p < 0.001$
- Coefficient = 0.299

Privacy protection significantly influences Trust, explaining 16.1% of variance. This is one of the strongest individual effects in the model, which highlights the importance of data security.

Regression Analysis – Model 4

Dependent Variables: Perceived Value and Trust

Independent Variable: Firm Reputation

Reputation → Perceived Value

- $R^2 = 0.180$
- Coefficient = 0.332
- $p < 0.001$

Reputation → Trust

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- $R^2 = 0.106$
- Coefficient = 0.251
- $p < 0.001$

Firm reputation significantly influences both mediators, with the strongest impact observed on perceived value.

Regression Analysis – Model 5

Dependent Variable: Adoption Intention

Independent Variables: Perceived Value, Trust

- $R^2 = 0.369$
- Model significance: $p < 0.001$

Variable	Coefficient	p-value
Perceived Value	0.308	<0.001
Trust	0.292	<0.001

The model explains 36.9% of the variance in adoption intention. Both perceived value and trust significantly and positively influence adoption intention, with nearly equal strength.

Mediation Analysis (Bootstrapped Indirect Effects)

To formally test the mediation implied by the conceptual model, bootstrapped mediation analysis (5,000 resamples, bias-corrected 95% confidence intervals) was conducted for each hypothesised indirect path, following the Preacher and Hayes (2004, 2008) approach. This complements the separate regression models above by directly testing whether Perceived Value and Trust carry the effect of the fiduciary predictors through to Adoption Intention.

Table. Bootstrapped mediation analysis results (N = 301, 5,000 resamples)

Path	Indirect Effect	95% CI	Direct Effect	Result
H1+H5a: Fiduciary Care → Perceived Value → Adoption Intention	0.136	[0.077, 0.203]	0.186 (sig.)	Partial mediation
H2+H5a: Personalization → Perceived Value → Adoption Intention	0.081	[0.033, 0.139]	0.115 (sig.)	Partial mediation
H3+H5b: Privacy Protection → Trust → Adoption Intention	0.102	[0.069, 0.142]	0.210 (sig.)	Partial mediation
H4a+H5a: Firm Reputation → Perceived Value → Adoption Intention	0.110	[0.076, 0.153]	0.229 (sig.)	Partial mediation
H4b+H5b: Firm Reputation → Trust → Adoption Intention	0.087	[0.055, 0.125]	0.252 (sig.)	Partial mediation

All five indirect effects were statistically significant, as their bias-corrected confidence intervals excluded zero, confirming that Perceived Value and Trust do mediate the relationships between the fiduciary predictors and Adoption Intention. In each case the direct effect also remained significant after accounting for the mediator,

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indicating partial rather than full mediation: the fiduciary predictors influence adoption intention both through the mediators and directly. This provides empirical support for the mediation structure proposed in the conceptual model in Section 3, rather than relying on the pattern of separate regression coefficients alone.

Moderation Analysis

Investment Experience was tested as a moderator between Trust and Adoption Intention.

- Interaction Coefficient = -0.009
- p = 0.877

The moderation effect is not statistically significant, which indicates that investment experience does not influence the trust–adoption relationship.

Regression Diagnostics

Beyond the multicollinearity check reported below, each regression model was further evaluated for coefficient precision (95% confidence intervals), residual normality (Jarque–Bera test), and homoscedasticity (Breusch–Pagan test).

Multicollinearity

Variance Inflation Factor (VIF) values were below 2 for all predictors, confirming the absence of multicollinearity. For Model 5, which includes two predictors, VIF = 1.36 for both Perceived Value and Trust. The regression estimates are therefore stable and reliable.

Coefficient Confidence Intervals

Table. Regression coefficients with 95% confidence intervals

Model	Predictor	b	95% CI	p
Model 1	Fiduciary Care	0.326	[0.192, 0.460]	< .001
Model 2	Personalization	0.186	[0.075, 0.296]	.001
Model 3	Privacy Protection	0.299	[0.222, 0.377]	< .001
Model 4a	Firm Reputation → Perceived Value	0.332	[0.251, 0.412]	< .001
Model 4b	Firm Reputation → Trust	0.251	[0.168, 0.334]	< .001
Model 5	Perceived Value	0.308	[0.218, 0.399]	< .001
Model 5	Trust	0.292	[0.201, 0.384]	< .001

Residual Normality and Homoscedasticity

Table. Residual diagnostics by model (N = 301)

Model	Jarque–Bera p	Breusch–Pagan p	Interpretation
Model 1	0.392	0.483	Normal, homoscedastic
Model 2	0.521	0.245	Normal, homoscedastic
Model 3	0.034	0.581	Mild non-normality, homoscedastic
Model 4a	0.472	0.265	Normal, homoscedastic
Model 4b	0.069	0.571	Normal, homoscedastic
Model 5	0.074	0.953	Normal, homoscedastic

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All models showed homoscedastic residuals (Breusch–Pagan $p > .05$), indicating that error variance was constant across predicted values. Residuals were approximately normally distributed for all models except Model 3 (Privacy Protection → Trust), which showed mild non-normality ($p = .034$). Given the sample size ($N = 301$), OLS coefficient estimates and standard errors remain asymptotically robust to this degree of non-normality, and the result is reported here for transparency rather than treated as a violation that invalidates the model.

Hypothesis Testing

Hypothesis	Decision
H1: Performance Efficacy (Fiduciary Care) positively influences Perceived Value.	Accepted
H2: Personalization (Duty to Inform) positively influences Perceived Value.	Accepted
H3: Privacy Protection (Fiduciary Loyalty) positively influences Trust.	Accepted
H4a: Firm Reputation positively influences Perceived Value.	Accepted
H4b: Firm reputation positively influences Trust.	Accepted
H5a: Perceived Value positively influences Adoption Intention.	Accepted
H5b: Trust positively influences Adoption Intention.	Accepted
H6: Investment Experience moderates the effect of Trust on Adoption Intention.	Rejected

Integrated Interpretation of Findings

The results show that there is a structured pathway in which fiduciary care and fiduciary loyalty operate through different psychological mediators. Firm reputation is the strongest predictor of perceived value, while privacy protection is the dominant predictor of trust.

Perceived value and trust combined; explain a major portion of adoption intention, which suggests that investors expect both economic and ethical assurance before adopting robo-advisory platforms.

The absence of moderation by investment experience implies that there is a universal reliance on trust across investor segments, which reinforces the central role of fiduciary loyalty in fintech adoption decisions.

DISCUSSION OF FINDINGS

This investigation provides systematic knowledge on the effect of fiduciary-oriented drivers on robo-advisor adoption among investors in Bangalore.

To begin with, the empirical data suggest that the firm reputation is strongly and statistically significantly associated with value perception **($R^2 = 18\%$)**, emerging as the strongest predictor within the value pathway. Such results indicate that the economic value of robo-advisory platforms is strongly associated with institutional credibility and brand name when determining its value according to investors. In a high risk financial environment, reputation acts as a heuristic indicator of competency.

Second, **privacy protection is significantly associated with trust ($R^2 = 16.1\%$)**, indicating that the issue of data security is at the center of trust development. Financial advisory work is a sensitive business that deals with both personal and transactional data and it seems that investors are more concerned with safe data management than strictly technical performance functions.

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Performance efficacy is also significantly associated with perceived value, but the level of its explanatory power (7.1%) is significantly lower than the level of the firm reputation. Personalization demonstrates a statistically significant but relatively small impact (3.5%) suggesting that customization can be taken as a feature and not a distinguishing attribute.

More importantly, the combination of perceived value and trust accounts to 36.9%of the variance in adoption intention which suggests that both economic and ethical confidence are relevant considerations when adopting the new system. Relative similarity of the beta coefficients of the perceived value (0.308) and trust (0.292) imply that financial benefits and integrity of the platform are very close in terms of weighting when it comes to adoption.

($\beta = 0.292$) suggests that investors weigh financial benefits and platform integrity almost equally when considering adoption.

However, it is surprising that investment experience does not moderate the trust-adoption relationship. This shows that trust is a common necessity cut across the boards of investors irrespective of the experience level. Overall, the results show that the adoption of robo-advisors in Bangalore can be explained not so much by strictly technological characteristics as by the manifestation of fiduciary loyalty (that is, privacy and reputation)

Theoretical Contributions

This research provides the body of knowledge in fintech and technology acceptance in three valuable ways.

First, its application introduces the fiduciary duty theory into the research of robo-advisors. Although the researches by earlier scholars rely more on TAM or UTAUT models, the present study defines fiduciary care and fiduciary loyalty as quantifiable behavioural indicators, thus augmenting the theoretical basis of fintech adoption with measurement variables beyond technological functionality.

Second, the results shed light on various roles of fiduciary dimensions. The most prominent predictor is reputation which is a key predictor of perceived value whereas the most significant is privacy protection as far as trust is concerned. The difference adds to the theoretical knowledge by showing that performance-oriented and ethics-oriented predictors are associated with different psychological mediators.

Third, the results of the study provide empirical support of joint and almost equal effect of the perceived value and trust on adoption intention. This supports the argument that the decision to adopt fintech in the context of financial advisory represents neither the rational nor the relational decision type but an integrated cognitive-ethical analysis level. Also, there is no evidence of moderation by investment experience, which is one of the assumptions that are often put forward in the adoption literature, and thus, trust requirements could be similar at any level of investor experience level.

Managerial Implications

The results provide valuable implications on the robo-advisory platform, fintech companies, and regulators in Bangalore. To start with, the companies must focus on the credibility of the brands and institutional signalling as reputation contributes greatly to the perceived value. This perception can be reinforced by strategic alliances or transparency of regulations and conspicuous levels of compliance certification.

Second, the protection of privacy is to be placed on the list of the key value propositions rather than a technical feature. Effective communication on encryption standards, regulatory protections and data usage policies can significantly increase the level of trust.

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Third, although the performance efficacy helps the value perception, it must be accompanied with the credibility signals. Reputational support may be necessary to instigate adoption when the technical superiority is not enough.

Fourth, since perceived value and trust are two variables associated with higher adoption intention, the companies ought to develop communication frameworks that incorporate both performance evaluation and ethical guarantees.

Lastly, the non-significant moderation result indicates that reliance on trust did not vary with investment experience in this sample, so investment experience should not be assumed to reduce trust-related concerns about platform reliance. Trust-building programs should be stressed out without discrimination among the categories of customers.

Limitations of the Study

The study also has limitations despite having meaningful contributions. To begin with, the sample was drawn using non-probability (convenience and snowball) sampling from investors based in Bangalore, so the findings should be understood as reflecting this specific sample rather than being statistically generalisable to other parts of India. The attitude of investors in metropolis fintech centres might not be the same as that in semi urban or rural markets.

Second, the cross-sectional design takes a single time perception of the perceptions. Because data were collected at a single point in time, the reported relationships should be interpreted as associations rather than causal effects; the direction and stability of these relationships cannot be established without longitudinal or experimental data. Technological innovations or changing policies may influence investor trust and change attitudes to the adoption of fintech.

Third, the research is based on questionnaires that are self-administered and can be subject to response bias or the social desirability effect.

Fourth, limited-item constructs were used to measure perceived value and trust. Multi-item tested scales can be applied in future studies to enhance the construct validity.

Fifth, the model is able to explain a significant part of the adoption intention (36.9%) but not other reasons like perceived risk, financial literacy or regulatory awareness that would contribute to the adoption behaviour.

Future Research Directions

This research leaves a number of gaps that can be explored. First, the current study can be extended in the future to include the geographical coverage to compare the patterns of fiduciary-based adoption in various cities in India or in emerging economies.

Second, some other constructs, including perceived risk, financial literacy, algorithm transparency, or regulatory trust can be added to create a more inclusive adoption framework.

Third, structural equation modelling (SEM) may be applied to test the complete mediation pathway at once and to test and estimate indirect effects on a firmer basis.

Fourth, the longitudinal study may be conducted on the changes in trust and perceived value as more time passes since the inception of exposure to the robo-advisor platform.

Fifth, experimental research involving a comparison of performance of a human advisor and a robo-advisor could help reveal additional information concerning the difference in fiduciary expectations to various types of advisory.

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CONCLUSION

This paper examines the factors driving the adoption of robo-advisors in Bangalore by combining the elements of fiduciary duty and technology acceptance models. The research is ethically motivated because the operationalization of the performance efficacy and personalization (fiduciary care) and the privacy protection and the firm image (fiduciary loyalty) allow the research to explain the adoption behavior of fintech. The results show that firm reputation is strongly associated with perceived value, and privacy protection is strongly associated with trust. Adoption intention is predicted by perceived value and trust, and therefore there is need to have economic and ethical certainty in investment decision-making processes. Extreme absence of moderation on the part of the investment experience suggests that trust is a common antecedent of adopting a robo-advisor. On the whole, the research contributes to the theory of fintech adoption because it indicates that fiduciary-congruent signals are significantly associated with investor perceptions and behavioral intentions in new digital monetary economies.

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