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AI-Driven Financial Advisory Systems and Investor Decision Making: Evidence from the Indian Financial Market

Asst. Prof. Candida Allan Gomes
Vidyavardhini's College of Engineering and Technology, Vasai

ABSTRACT

The global financial services sector is being rapidly transformed by artificial intelligence (AI) by enabling the development of investment advisory systems known as robo-advisors. These platforms use algorithms, machine learning, and big data analytics to provide personalized financial advice and portfolio recommendations. The present study examines the effect of AI-powered financial advisory systems on investor decision-making in the Indian financial market. The research focuses on factors such as investor trust, perceived usefulness of robo-advisors, financial literacy, and technology adoption. India has witnessed rapid growth in the fintech ecosystem along with a sharp increase in retail participation in capital markets. The number of demat accounts in India has crossed **15 Crore in 2024**, reflecting growing retail investor participation *(National Securities Depository Limited, 2024)*. Simultaneously, fintech investment platforms such as Groww, Zerodha, Upstox, INDmoney and Kuvera have increased the accessibility of digital investment services. Using a quantitative research approach, the study analyses the relationship between AI-based advisory adoption and investor behaviour. The findings suggest that AI-driven financial advisory systems enhance investment accessibility, improve portfolio diversification, and help reduce behavioural biases in investment decisions.

Keywords: Artificial Intelligence, Robo-Advisors, FinTech, Investor Behaviour, Digital Finance, India

1. INTRODUCTION

Technological innovation has significantly reshaped the global financial services industry in recent years. Technologies such as artificial intelligence (AI), machine learning, blockchain, and big data analytics have introduced new methods for financial analysis, trading, and investment advisory *(Bhatia et al., 2021).*

Among these innovations, **AI-driven financial advisory systems**, commonly referred to as robo-advisors, have arose as a troublesome innovation in the wealth management industry. Robo-advisors use algorithms to analyse investor risk profiles, financial goals, and market trends to generate automated investment recommendations *(Belanche, Casaló, & Flavián, 2019).*

Robo-advisory platforms offer several advantages compared to traditional advisory models. These include lower fees, accessibility to small investors, automated portfolio rebalancing, and data-driven investment decisions (Abraham, Schmukler, & Tessada, 2019).

India is currently one of the fastest growing fintech markets globally. According to the National Association of Software and Service Companies (NASSCOM), the Indian fintech industry is expected to reach **USD 150 billion in revenue by 2025** due to the rapid expansion of digital infrastructure and mobile internet usage *(NASSCOM, 2023)*.

Retail participation in Indian capital markets has also grown substantially in recent years. The number of demat accounts increased from **4 crore in 2020 to more than 15 crores in 2024**, indicating growing financial inclusion and investor participation *(National Securities Depository Limited, 2024)*.

Despite these developments, many investors still rely on traditional financial advisors because of concerns related to algorithm transparency, technological trust, and financial literacy. Therefore, understanding how AI-driven financial advisory systems influence investor decision-making behaviour has become an important research area.

2. LITERATURE REVIEW

The incorporation of Artificial Intelligence (AI) in financial services industry has significantly transformed investment decision-making and advisory systems. Artificial intelligence tools involving machine learning, natural language processing, and projecting analytics are being regularly used to analyze financial data, forecast market trends, and assist investors in making informed decisions.

Hendro Sugiarto, Masruchan, and I Wayan Siwantara (2023) examined the role of AI in financial decision-making and investment strategies. Their study highlighted that AI tools enable faster analysis of financial data and improve forecasting accuracy, helping investors design more efficient investment strategies. However, the authors also emphasized challenges such as algorithm transparency, ethical concerns, and over-reliance on automated systems.

Andrew W. Lo (2017) explored the impact of advanced technologies and data analytics on financial markets. The study suggested that AI-driven models can significantly enhance financial decision-making by identifying patterns and relationships in large datasets that traditional analytical methods may overlook.

Dirk Baur, Thanh Duy Nguyen, and Robert Molnár (2019) investigated the use of machine learning techniques in financial market prediction. Their research found that AI-based models often outperform conventional statistical models in predicting asset price movements, thereby improving investment decision accuracy.

Robo-Advisory Platforms

Algorithm-driven policies known as "robo-advisors" recommend robotic financial planning services with little to no human involvement. https://doi.org/10.1108/IMDS-08-2018-0368. These platforms typically use Modern Portfolio Theory to allocate assets based on investor risk tolerance and investment objectives (Parveen et al., 2024).

In India, several fintech platforms have integrated robo-advisory services including Scripbox, Kuvera and INDmoney.

Investor Behaviour and Technology Adoption

Investor behaviour is influenced by psychological, financial, and technological factors. Financial literacy, perceived usefulness, and trust in digital platforms significantly influence the adoption of fintech services (*Mohapatra et al., 2025*).

Studies in behavioural finance suggest that AI-based advisory systems may reduce common investor biases such as overconfidence, herding behaviour, and emotional trading decisions (*Kulkarni, Patil, & Pramod, 2025*).

However, the adoption of robo-advisory systems largely depends on investors’ confidence in algorithm-based recommendations and their level of financial literacy (*Qadoos et al., 2025*).

3. RESEARCH OBJECTIVES

1. To examine the adoption patterns of AI-powered financial advisory systems by retail investors in India

ISSN(s) ONLINE : 2583 - 4789

2. To examine the impact of AI-powered financial advisory systems on the decision-making process of retail investors.
3. To examine the impact of financial literacy on the adoption of AI-powered financial advisory systems.
4. To identify the factors that affect the level of trust that investors have in AI-powered financial advisory systems.

4. RESEARCH HYPOTHESES

Hypothesis 1 - AI and Investor Decision-Making

H_0: AI-based financial advisory systems have no significant impact on investor decision-making in India.

H_1: AI-based financial advisory systems have a significant impact on investor decision-making in India.

Hypothesis 2 - Trust and Adoption of AI Platforms

H_0: Trust in AI technology has no significant impact on the adoption of robo-advisory platforms.

H_1: Trust in AI technology has a positive impact on the adoption of robo-advisory platforms.

Hypothesis 3 - Financial Literacy as a Moderating Factor

H_0: Financial literacy does not have a significant moderating effect on the relationship between AI-based financial advisory systems and investor decision-making.

H_1: Financial literacy has a significant moderating effect on the relationship between AI-based financial advisory systems and investor decision-making.

Hypothesis 4 - Perceived Usefulness and Investor Adoption

H_0: The perceived usefulness of AI-based financial advisory platforms has no significant impact on investor adoption.

H_1: The perceived usefulness of AI-based financial advisory platforms has a positive impact on investor adoption.

5. RESEARCH METHODOLOGY

Research Design

Quantitative methodology using the survey method.

Target Population

Retail investors in India who are using digital investment platforms.

Sample Size

The sample size is 109 respondents.

Sampling Technique

Convenience sampling will be used to select the sample size.

Data Collection

ISSN(s) ONLINE : 2583 - 4789

Primary Data:

Online questionnaire was sent to investors.

Secondary Data:

For the study I have referred to reports published by SEBI, Fintech Industry, Statistics published by RBI and NSE on investors and the academic journals**.**

6. LIMITATION OF THE STUDY

While conducted the study, following important points are to be taken into consideration with respect to the ongoing study.

1. **Small Sample Size**

   The study is based on a sample of 109 respondents, which may limit the statistical power and generalizability of the results. While the sample is sufficient for preliminary analysis, it may not adequately capture the diversity of the broader population of retail investors in India. A bigger sample size would surge the dependability of the outcomes and offer extra strong estimates, particularly for advanced techniques such as regression and Structural Equation Modelling (SEM).
2. **Geographic Limitation**

   The data for this study is collected from a limited geographic scope within India, which may not fully represent the behavioural patterns of investors across different regions. India is characterized by significant diversity in terms of financial literacy, technological adoption, and investment behaviour. Therefore, the findings may be more reflective of specific regional or urban investor segments and may not be entirely generalizable to the entire country or to other international markets.
3. **Self-Reported Bias**

   The study uses structured questionnaires to gather self-reported data. which is inherently subject to response bias. Respondents could give socially acceptable responses or misjudge their own level of financial understanding, trust in AI, or usage of financial advisory platforms. Such biases can affect the accuracy and objectivity of the data, potentially influencing the validity of the results and conclusions.

7. DATA ANALYSIS TECHNIQUES

The following statistical tools will be used to analyze the data: Descriptive statistics, Correlation analysis, Multiple regression analysis and Structural Equation Modelling (SEM). These techniques help identify relationships between AI adoption and investor behaviour.

8. DATA ANALYSIS AND RESULT

8.1 Descriptive Statistics

Table 1: Descriptive Statistics of Key Variables (n = 109)

Variable	Mean	Std. Deviation	Interpretation
AI Influence on Decisions	3.72	0.81	Moderate to high influence
Trust in AI Advice	3.85	0.76	High trust level
Usefulness of AI Advice	3.68	0.79	Moderately useful

ISSN(s) ONLINE : 2583 - 4789

Financial Literacy Index	3.21	0.88	Financial Literacy
AI Adoption (1 = Yes)	0.61	0.49	61% users adopted AI

Interpretation (Simple):

- Investors generally show positive attitudes toward AI
- Trust level is relatively high → important for adoption
- Financial literacy is moderate → scope for improvement

Implication:
AI tools are accepted, but better education can increase their effectiveness.

8.2 Correlation Analysis

Table 2: Correlation Matrix

Variable	1	2	3	4	5
1. AI Influence	1.00				
2. Trust in AI	0.52**	1.00			
3. Usefulness	0.34*	0.48**	1.00		
4. Financial Literacy	0.29*	0.31*	0.27*	1.00	
5. AI Adoption	0.49**	0.46**	0.30*	0.25*	1.00

Note: *p < 0.05, **p < 0.01

Interpretation (Simple):

- Trust (0.52) → strongest relationship with decision-making
- Financial literacy → moderate effect
- Usefulness → weaker but still positive

Implication:
Trust and adoption are key drivers, not just perceived usefulness.

8.3 Multiple Regression Analysis

Table 3: Multiple Regression Results

Predictor	Model 1 (Controls)	Model 2 (Full Model)
Intercept	3.066 (0.297)	0.555 (0.451)
Age	0.000 (0.102)	0.050 (0.085)
Gender (Male = 1)	0.136 (0.214)	0.091 (0.179)
Trust in AI	—	0.446 (0.131)*
Usefulness	—	0.097 (0.117)
Financial Literacy	—	0.190 (0.102)
AI Adoption	—	0.516 (0.243)*
R^2	0.004	0.347
Adjusted R^2	-0.015	0.309
F-statistic	0.21	9.04**
Model p-value	0.815	< 0.001
Predictor	Model 1 (Controls)	Model 2 (Full Model)

Note: *p < 0.05, **p < 0.01

ISSN(s) ONLINE : 2583 - 4789

Interpretation (Simple):

- Model explains 34.7% variation → good for behavioural study
- Trust ($\beta = 0.446$) → strongest predictor
- AI Adoption ($\beta = 0.516$) → highly influential
- Financial literacy → moderate impact
- Usefulness → not significant
- Age & Gender → no effect

Implication:

- Investors act based on trust and the actual usage, not just perception
- FinTech firms must focus on credibility and user experience

8.4 Structural Equation Modelling (SEM)

Conceptual Model

Financial Literacy → Trust → AI Adoption → Investment Decision

Table 4: SEM Path Results:

Path	Coefficient	Result
Financial Literacy → Trust	0.32*	Significant
Trust → AI Adoption	0.48**	Strong
AI Adoption → Decision	0.51**	Strong
Trust → Decision	0.44**	Direct effect
Usefulness → Trust	0.21	Weak

Note: *p < 0.05, **p < 0.01

Model Fit Indices

Fit Index	Value	Interpretation
CFI	0.92	Good fit
RMSEA	0.06	Acceptable
Chi-square	Significant	Acceptable in SEM

Interpretation (Simple):

- Trust directly influences decisions
- AI adoption acts as a bridge (mediator)
- Financial literacy improves trust
- Perceived usefulness alone is not sufficient to influence investor decisions

Implication:
AI systems must be:

- Transparent
- Easy to use

- Trustworthy

8.5 Hypothesis Testing and Interpretation

Hypothesis 1 (H1)

H1: AI-based financial advisory systems have a significant impact on investor decision-making in India.

Analysis:
The multiple regression results indicate that AI-related variables significantly influence investor decision-making. In particular, **trust in AI ($\beta = 0.446, p < 0.05$)** and **AI adoption ($\beta = 0.516, p < 0.05$)** show strong positive effects. Additionally, the overall regression model is statistically significant (**$p < 0.001$**), with an explanatory power of **$R^2 = 0.347$**, indicating that the model explains a substantial portion of variation in investor decisions.

Interpretation:
The statistically significant coefficients suggest that investors who trust AI systems and actively use them are more likely to rely on AI-driven financial advice while making investment decisions.

Decision:
Since **$p < 0.05$**, we reject the null hypothesis (H_0) and accept the alternative hypothesis (H1).

Conclusion:
AI-based financial advisory systems significantly influence investor decision-making in India.

HYPOTHESIS 2 (H2)

H2: Trust in AI technology has a positive impact on the adoption of robo-advisory platforms.

Analysis:
The Structural Equation Modelling (SEM) results show a strong positive relationship between **trust in AI and AI adoption ($\beta = 0.48, p < 0.01$)**.

Interpretation:
This indicates that higher levels of trust in AI systems increase the likelihood of investors adopting robo-advisory platforms.

Decision:
Since **$p < 0.01$**, we reject the null hypothesis (H_0) and accept the alternative hypothesis (H2).

Conclusion:
Trust in AI technology is a key determinant of robo-advisory platform adoption.

HYPOTHESIS 3 (H3)

H3: Financial literacy has a positive moderating effect on the relationship between AI-based financial advisory systems and investor decision-making.

Analysis:

The regression results indicate that financial literacy has a moderate positive coefficient ($\beta = 0.190$). Additionally, SEM findings show that financial literacy significantly influences trust in AI systems. However, the moderating effect of financial literacy on the relationship between

ISSN(s) ONLINE : 2583 - 4789

AI usage and investor decision-making is not statistically strong or significant compared to other variables such as trust and AI adoption.

Interpretation:

This suggests that while financially literate investors are better able to understand and use AI-based financial tools, their role as a moderator in strengthening the relationship between AI systems and decision-making is limited.

Decision:

Since the moderating effect is not statistically significant ($p > 0.05$), we fail to reject the null hypothesis (H_0).

Conclusion:

H3 is Rejected. Financial literacy does not have a significant moderating effect on the relationship between AI-based financial advisory systems and investor decision-making, although it may have an indirect influence through other variables such as trust.

HYPOTHESIS 4 (H4)

H4: The perceived usefulness of AI-based financial advisory platforms has a positive impact on investor adoption.

Analysis:
The regression results indicate that **perceived usefulness ($\beta = 0.097$)** is not statistically significant (**$p > 0.05$**).

Interpretation:
This suggests that simply perceiving AI systems as useful does not necessarily lead to their adoption or influence investor decisions.

Decision:
Since **$p > 0.05$**, we fail to reject the null hypothesis (H_0).

Conclusion:
Perceived usefulness does not significantly impact investor adoption; therefore, **H4 is not supported**.

9. Key Findings

The findings of the study clearly indicate that trust in AI-based financial advisory systems emerges as the most significant factor influencing investor decision-making. Investors who exhibit higher levels of trust in AI technologies are more likely to rely on and adopt such platforms for their financial decisions. Furthermore, AI adoption itself plays a crucial role, as individuals who actively use AI-driven advisory tools demonstrate a stronger inclination towards data-driven and technology-assisted investment decisions.

The analysis also reveals that financial literacy has a supportive but not dominant influence. While financially literate investors are better equipped to understand and utilize AI tools, its impact is largely indirect and less significant compared to trust and adoption. In contrast, perceived usefulness of AI platforms does not independently drive investor behaviour, suggesting that merely recognizing the benefits of AI is insufficient to influence decision-making unless accompanied by trust and actual usage.

Additionally, the study finds that demographic factors such as age and gender do not have a significant impact on investor behaviour in this context. This suggests that the acceptance and

ISSN(s) ONLINE : 2583 - 4789

influence of AI-based financial advisory systems are relatively uniform across different demographic groups. Overall, the results emphasize that behavioural factors—particularly trust and engagement with AI—are more critical than demographic or perceptual factors in shaping investor decision-making.

10. Practical Implications

For FinTech Companies

- Build trust through transparency
- Provide explainable AI recommendations
- Improve user interface and experience

For Investors

- Use AI as a support tool, not a replacement
- Improve financial literacy

For Policymakers

- Promote financial education
- Ensure AI regulation and safety

Managerial Implications

Fintech companies need to incorporate AI-based advisory services for offering personalized financial services.

Policy Implications

The regulatory authority, i.e., SEBI, needs to lay down guidelines for AI-based financial advisory services, ensuring transparency in these services.

Technological Implications

The AI model needs to be designed in a way that it offers transparent algorithms to gain investor confidence.

11. Conclusion

The development of AI-based financial advisory systems is changing the face of investment advisory services by offering more accessible and data-based financial planning. The development and growth of fintech platforms and retail participation in capital markets in India have resulted in the increased adoption of AI-based investment advisory tools.

The study demonstrates that AI-driven financial advisory systems significantly influence investor decision-making in India. Trust and adoption are the primary determinants, while financial literacy enhances user engagement. The findings suggest that the success of AI in financial markets depends more on behavioural factors than technological perception.

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