

## FACTORS INFLUENCING AI AND HUMAN ADVISOR DECISIONS IN THE INDIAN FINANCIAL MARKET: A RETAIL CONSUMER ANALYSIS

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### ABSTRACT

**Purpose** – This study aims to examine the factors influencing Indian retail investors' preferences, trust, and decision-making when choosing between AI-driven and human financial advisors. It focuses on how perceived opportunities and threats affect the intention to use AI-advisory services in the context of India's rapidly digitalizing financial landscape.

**Design/methodology/approach** – The research uses a cross-sectional survey design, collecting data from 145 Indian retail investors through an online structured questionnaire. A two-step Partial Least Squares Structural Equation Modeling (PLS-SEM) approach is applied to analyze the influence of perceived opportunities (e.g., cost-effectiveness, convenience, personalization) and perceived threats (e.g., lack of trust, data privacy threats, limited human interaction) on adoption intentions.

**Findings** – The results show a significant positive relationship between perceived opportunities and the intention to use AI-advisors, while perceived threats have a significant negative impact. Younger, financially literate male investors (aged 20–35, postgraduate level, and earning ₹75,000+ per month) are more likely to adopt AI-advisory platforms. The study also highlights the potential of AI-advisory tools to enhance financial inclusion in India.

**Research limitations/implications** – The study is limited by its sample size and geographic scope, which may affect the generalizability of the findings. Future research could explore longitudinal data or include a more diverse respondent pool across regions and financial backgrounds.

**Practical implications** – Insights from this research can help financial institutions, fintech startups, and policymakers tailor AI-advisory services to better align with consumer expectations, particularly by addressing trust and privacy threats. It also emphasizes the need for regulatory frameworks to ensure responsible AI deployment.

**Keywords:** Artificial Intelligence-Advisors, Indian Financial Market, Retail Investors, Fintech, Consumer Behavior

### INTRODUCTION

The Indian financial sector has witnessed the emergence of robo-advisory as a notable FinTech innovation, driven by rapid digitalisation and the growing influence of AI-based automation<sup>1</sup>. This technological advancement marks a shift from traditional financial advisory services, attracting a new segment of tech-savvy retail investors while also reshaping the expectations of existing clients<sup>2</sup>. Compared to traditional advisory models, robo-advisory offers greater accessibility and affordability, especially for investors with limited capital<sup>3</sup>. Conventional advisors in India have historically concentrated on high-net-worth individuals, often overlooking small savers due to lower revenue potential<sup>4</sup>. Robo-advisors are filling this gap by offering tailored financial solutions to young, low-to-middle-income earners, particularly millennials, and are gradually extending their services to wealthier clients as well<sup>5</sup>. Functioning as internet-based platforms, robo-advisors use automated algorithms to assess investor profiles, allocate assets, and periodically rebalance portfolios, aiming for optimal returns aligned with each client's risk appetite<sup>6</sup>. These platforms primarily target private investors who either rely on self-judgment or seek advice from peers, family, or digital sources. Typically, investors complete an online risk-profile questionnaire, which forms the basis for a customized portfolio aligned with regulatory standards and client goals<sup>7</sup>.

India presents a compelling environment to explore the adoption of robo-advisory services. With one of the highest savings rates in Asia and growing financial awareness among the middle class, Indian investors are increasingly seeking alternatives to traditional saving instruments, including

Exchange Traded Funds (ETFs) and automated advisory platforms<sup>8</sup>. The prolonged low-interest rates on fixed deposits and recurring deposits have further pushed retail investors—particularly millennials—towards tech-enabled solutions like robo-advisors<sup>9</sup>. In light of these developments, this study aims to understand how receptive Indian investors are to engaging with AI-powered robo-advisors instead of conventional human advisors<sup>10</sup>. The research investigates the perceived opportunities and threats that shape Indian retail investors' intentions to adopt robo-advisory services, categorizing this FinTech innovation as a disruptive force in the financial advisory landscape<sup>11</sup>.

The main objective of this study is to analyze the factors influencing Indian retail consumers' decisions in selecting robo-advisors over human advisors. The sub-objectives include:

- Identifying the key opportunities retail banking consumers perceive when opting for robo-advisors
- Identifying the key threats retail banking consumers associate with robo-advisors

For robo-advisors to build trust in the Indian market, it is essential to offer clear, transparent information regarding their algorithms, investment methodologies, fees, and associated risks<sup>12</sup>. Indian consumers also demand clarity and control over how their financial data is processed and protected<sup>13</sup>. To earn and retain user trust, robust cybersecurity measures must be implemented to prevent unauthorized access to personal and financial information<sup>14</sup>. While investment processes have been simplified through digital platforms, some users—especially those with limited financial literacy—still find robo-advisory tools complex or intimidating<sup>15</sup>.

The Indian financial advisory landscape is undergoing a transformation with the rapid rise of robo-advisors—AI-powered platforms that offer low-cost, algorithm-driven investment solutions. As India's FinTech market continues to expand, valued at ₹2.3 lakh crore in 2023 and projected to grow at a CAGR of 31% through 2027, consumer preferences are shifting toward more efficient, tech-enabled financial services<sup>16</sup>. Understanding investor behavior is essential for policymakers, FinTech firms, and regulators to design services aligned with evolving user expectations and to build sustainable trust in digital finance<sup>17</sup>. The findings from such research will empower industry stakeholders to enhance platform credibility, deliver tailored services, and advance financial inclusion through robo-advisory models.

Positive customer experiences and trust play a pivotal role in encouraging adoption of robo-advisors in India, particularly among millennials and first-time investors in Tier 2 and Tier 3 cities<sup>18</sup>. In contrast, poor user experience or perceived risks—such as lack of human guidance or data privacy threats—can diminish investor confidence and slow adoption. In a highly competitive Indian FinTech market with a growing number of robo-advisory platforms, customer satisfaction and personalization have emerged as key differentiators<sup>19</sup>. Companies that prioritize user-centric design and transparent financial guidance are more likely to attract and retain investors, especially from underserved demographic segments such as young salaried professionals and self-employed individuals<sup>20</sup>.

Evaluating the influence of perceived threats on user intention can provide actionable insights for improving platform credibility and reshaping investment behavior<sup>21</sup>. Lower perceived risk, particularly in comparison to traditional investment methods, can increase investor willingness to use robo-advisors. As these platforms grow in reach, their reputation will increasingly depend on how well they mitigate perceived risks while delivering consistent, compliant investment advice<sup>22</sup>.

Despite the growing popularity of robo-advisory in India, academic research in this area remains limited. There is a lack of comprehensive studies analyzing how socio-demographic variables—such as income, education level, gender, and investment experience—interact with behavioral aspects like risk tolerance and trust in automation<sup>23</sup>. Empirical research focusing on micro-level investor behavior in India is needed to close this gap and inform the development of more inclusive, transparent, and efficient robo-advisory services<sup>24</sup>.

### ***Literature Review:***

### **Impact of Opportunities on the Intention to Use Robo-Advisors**

Several studies have explored how robo-advisors are gaining ground in wealth management, especially in emerging economies like India, where digital financial adoption is rapidly increasing. As of 2023, India had over 125 million online investors, with platforms like Zerodha and Groww witnessing record-breaking user growth, indicating rising acceptance of automated investing tools<sup>25</sup>. The success of robo-advisory platforms hinges on collaborative innovation across legal, technical, and behavioural domains to ensure robust and regulated systems<sup>26</sup>. These platforms offer scalability, algorithmic efficiency, and reduced transaction costs, which make them financially viable, particularly for cost-sensitive Indian investors<sup>27</sup>.

Robo-advisors in India are simplifying the investment process by reducing entry barriers—offering passive, low-fee portfolio management, easy onboarding via mobile apps, and remote portfolio access for new investors with limited financial knowledge<sup>28</sup>. With growing mobile penetration (over 80% smartphone users in urban areas) and financial literacy efforts, young investors increasingly prefer digital channels. Research indicates that robo-advisory services in India will continue expanding in size, client base, and technological sophistication, driven by social change and rising fintech competition<sup>29</sup>.

**H1: There is a significant impact of perceived opportunities on the intention to use robo-advisors.**

### **Impact of Threats on the Intention to Use Robo-Advisors**

Major Indian financial institutions, including HDFC Securities and ICICI Direct, are incorporating robo-advisory into their digital wealth management offerings as part of broader fintech transformation strategies<sup>30</sup>. However, the market faces challenges related to investor trust and data privacy. A substantial portion of Indian retail investors—especially first-time or young investors aged 18–29—lack sufficient expertise in making financial decisions, prompting them to seek external advice<sup>31</sup>. Their limited incomes make AI-powered robo-advisors an appealing, low-cost alternative to human consultants<sup>32</sup>.

At the same time, robo-advisors in India collect sensitive financial and personal data to customize investment strategies. This raises threats about cybersecurity and data protection. According to a 2023 report, **over 70%** of Indian investors cite data privacy as a top threat when using fintech platforms<sup>33</sup>. Cyber threats and breaches can not only result in financial loss but also damage the credibility of robo-advisory firms, further affecting user adoption<sup>34</sup>. Thus, understanding how perceived threats influence investor intentions is critical for platform development and regulatory frameworks.

**H2: There is a significant impact of perceived threats on the intention to use robo-advisors.**

### **Research Methodology:**

This study adopts a non-probability sampling method, specifically using purposive sampling to ensure inclusion of Indian retail investors with relevant experience in both human and AI-based financial advisory services<sup>34</sup>. This technique enables focused data collection from individuals capable of offering insights into digital advisory adoption. The target population includes urban retail investors across metros and Tier 1 cities who have either used or explored robo-advisors and traditional advisors. The sampling approach supports diversity and richness in responses, aligned with the study's objective of identifying factors influencing advisory choices<sup>35</sup>.

The survey was conducted between January 1 and January 20, 2024, using Google Forms and distributed via LinkedIn, WhatsApp, and investor forums. The questionnaire included demographics, investment habits, and perceptions of robo-advisory services. A five-point Likert scale was used, where 1 = strongly disagree and 5 = strongly agree. Participants voluntarily consented to take part in the study, and their anonymity was strictly maintained throughout<sup>36</sup>.

### **Survey Sections Included:**

- **Demographics:** gender, age, education, income

- **Robo-Advisory Usage:** frequency of robo-advisor usage, security types, motivations
- **Opportunities (O1–O8):** usefulness, goal attainment, ease of use, learning, financial outcomes
- **Threats (TH1–TH3):** fear of loss, perceived risk, lack of control
- **Intention (I1–I6):** willingness to share data, trust level, risk readiness

Items were randomly coded to minimize common method bias. The study applies the PLS-SEM (Partial Least Squares Structural Equation Modelling) technique using SmartPLS version 4, which is ideal for exploratory research involving both formative and reflective constructs, especially in markets like India where data normality is often a threat<sup>3</sup>.

The **two-step PLS-SEM** process was followed:

1. **Measurement Model Assessment:** Validity (convergent, discriminant), reliability, composite reliability
2. **Structural Model Evaluation:** Testing hypotheses and predictive strength<sup>38</sup>

PLS-SEM outperforms covariance-based SEM in terms of handling complex models and predicting latent variables, especially in emerging markets and behavioral research. It enables robust theory development in digitally transforming economies like India<sup>39</sup>.

Participants were fully informed about the purpose of the study, and ethical safeguards such as informed consent, confidentiality, and voluntary participation were strictly adhered to. To minimize bias, about 10% anonymous responses were included to ensure representativeness<sup>40</sup>.

### **Survey Design and Distribution**

The survey was created using Google Forms and shared between January 1 to January 20, 2024. This 20-day window allowed enough time to collect meaningful data while avoiding survey fatigue.

#### ***The survey included four sections:***

##### **1. Demographic Information:**

Gender, age, education level, and monthly savings.

##### **2. Robo-Advisory Experience:**

Whether the participant currently or previously invested in financial securities like stocks, mutual funds, ETFs, etc. It also asked about the frequency of buying/selling through robo-advisors and reasons for choosing them.

##### **3. Dependent Variable – Intention to Use AI-Advisors**

Measured through **six items**:

- **I1:** Willingness to use robo-advisors in the future
- **I2:** Likelihood of using them in the next 6 months
- **C1:** Willingness to share personal and sensitive data with robo-advisors
- **C2:** Belief in robo-advisors' trustworthiness
- **C3:** Trust in the financial advice/portfolio suggestions
- **C4:** Willingness to take risks when using robo-advisors

##### **4. Independent Variables**

- **Opportunity (8 items)** — These questions examined how robo-advisors are useful, including:

- **F1:** Helping make financial decisions
- **F2:** Increasing chances of reaching financial goals
- **F3:** Improving financial performance
- **F4:** Saving time
- **S1–S4:** Ease of use, user interaction, learning, and skill-building using robo-advisors

- **Threat (3 items)** — These items focused on:

- **CO1:** Viewing robo-advisors as a threat rather than a useful tool
- **CO2:** Perceived risks (like poor advice or loss of control)
- **CO3:** Fear of losing money using these platforms

**FINDINGS:**

**Descriptive Analysis**

The descriptive statistics in Table 1 show that the mean of most constructs is near 3, indicating a neutral stance among Indian retail investors when evaluating AI- or human-based financial advisory services.

**Table 1: Descriptive Statistics**

Construct	N	Mean	Std. Deviation
I1	145	3.14	1.136
I2	145	2.77	1.286
T1	145	2.65	1.357
T2	145	2.94	1.171
T3	145	2.99	1.155
T4	145	2.93	1.206
S1	145	3.10	1.145
S2	145	3.30	1.120
S3	145	3.46	1.118
S4	145	3.30	1.186
O1	145	3.26	1.098
O2	145	3.27	1.126
O3	145	3.19	1.168
O4	145	3.06	1.153
TH1	145	2.57	1.091
TH2	145	2.99	1.024
TH3	145	2.75	1.044

**Table 2: Investment in Securities**

Investment Status	Current Investment	Past Investment
Yes	55.9% (81)	62.8% (91)
No	44.1% (64)	37.2% (54)

**Explanation:** Over half of Indian respondents currently invest in securities. A slightly larger proportion had invested in the past, suggesting temporary withdrawal or market hesitation.

**Table 3: Frequency of Trading Securities**

Frequency	Buying (%)	Selling (%)
Less than once/year	47.6	62.1
Once per year	9.7	11.7
2–6 times per year	16.6	13.8
7–12 times per year	13.8	6.2
More than 24 times/year	9.7	4.1
Daily	2.8	2.1

**Explanation:** Most Indian retail investors trade infrequently, reflecting either a long-term investment mindset or limited market exposure.

**Table 4: Reason for Choosing Robo-Advisors**

Reason	% Respondents
Comfortable with AI	26.2%
Prefer making own analysis	34.5%
Rely on others'	17.2%

recommendations	
Other	22.1%

**Explanation:** A significant portion of Indian investors appreciate robo-advisors for the autonomy they provide in decision-making.

**Table 5:** Robo-Advisory and Demographics

Demographic	Robo-Advisory (%)	Investment (%)
<b>Gender</b>		
Male	11.0	47.6
Female	8.3	31.0
<b>Age Group</b>		
18–35	13.8	73.8
36–50	6.2	4.1
Over 50	1.4	0.7
<b>Education Level</b>		
High School	1.4	1.4
Bachelor's	8.0	22.1
Master's	12.4	54.5
<b>Monthly Savings (₹)</b>		
< ₹1000	4.8	7.6
₹1000–₹3000	1.4	10.3
₹3001–₹5000	6.2	18.6
₹5001–₹10,000	6.9	18.6
> ₹10,000	4.8	4.8

**Explanation:** Robo-advisory adoption is higher among young, male, educated Indians with higher savings capacity.

**Tables 6:** Validity & Reliability

Construct	AVE	Cronbach's Alpha	Composite Reliability
Intention to use AI	0.741	0.930	0.945
Opportunities	0.726	0.946	0.955
Threats	0.641	0.741	0.842

**Explanation:** All measurement constructs are internally reliable and valid for Indian respondents.

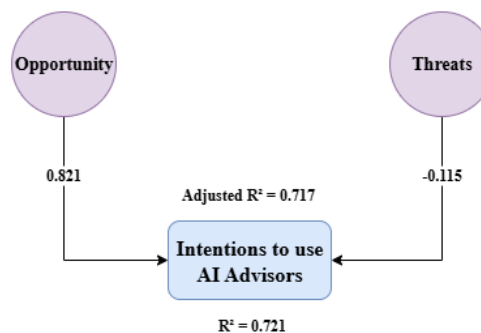
**Table 07:** Structural Model & Hypothesis Testing

Hypothesis	Path Coeff.	T-value	P-value	VIF	Decision
Opportunities → Intention to use AI	0.821	26.399	0.000	1.034	Accepted
Threats → Intention to use AI	-0.115	2.613	0.009	1.034	Accepted
<b>R<sup>2</sup> = 0.721</b>	<b>Adjusted R<sup>2</sup> = 0.717</b>				

**Explanation:** In India, perceived opportunities strongly and positively impact AI adoption in finance. Perceived threats reduce intent but still play a significant role.

This study uses Smart PLS 4 software to estimate PLS-SEM as shown in Figure 1 for path analysis.

PLS - SEM Model: Intentions to use AI Advisors



## CONCLUSION

This study, explored how Indian retail investors perceive and adopt robo-advisory services compared to traditional human financial advisors. The findings offer rich insights into behavioral patterns, demographic tendencies, and the statistical relationships influencing investor decisions.

The descriptive statistics revealed that most constructs had average scores near the neutral point (mean  $\approx 3.0$ ), indicating that Indian investors are neither strongly in favor of nor entirely against using robo-advisors. This neutrality reflects a transitional mindset where awareness of AI in finance exists, but full trust and adoption are still evolving.

Investment behavior analysis showed that 55.9% of respondents currently invest in financial securities, and 62.8% have invested in the past. However, the majority of investors trade infrequently—less than once per year—suggesting a long-term investment approach or limited active engagement with the market. Such behavior is typical of cautious investors who may lack time, expertise, or confidence to manage frequent trades.

When it comes to selecting robo-advisors, the highest proportion of respondents (34.5%) indicated a preference for conducting their own analysis with the support of AI tools. Another 26.2% found robo-advisors comfortable and convenient. These results point to a growing interest in technology-assisted investing, particularly among individuals who value decision-making autonomy. Meanwhile, reliance on third-party recommendations or other reasons accounted for the remaining portion, highlighting a mixed but positive attitude toward AI in financial decision-making.

Demographic analysis showed that the majority of robo-advisor users were males, aged between 18–35 years, and holding postgraduate or graduate degrees. Additionally, individuals with higher monthly savings demonstrated greater engagement with robo-advisory platforms. This suggests that younger, financially literate, and higher-income segments in India are more open to adopting AI-driven financial tools, while adoption among females, older age groups, and lower-income or less-educated populations remains limited.

The measurement model was statistically robust, as all constructs met the necessary thresholds for reliability and validity. Cronbach's alpha and composite reliability scores for all variables were well above 0.9, and Average Variance Extracted (AVE) scores confirmed convergent validity. Discriminant validity was also established, ensuring the model's accuracy in measuring distinct factors.

Finally, the structural model results showed that **perceived opportunities** had a strong and significant positive influence on the intention to use robo-advisors (path coefficient = 0.821,  $p < 0.01$ ). In contrast, **perceived threats** had a weaker but still significant negative impact (path coefficient = -0.115,  $p < 0.01$ ). The R-squared value of 0.721 indicates that 72.1% of the variance in investor intention can be explained by the constructs used in the model, confirming a substantial model fit.

In summary, the findings suggest that Indian retail investors are cautiously optimistic about using AI-based financial advisory tools. Their decisions are heavily influenced by perceived benefits such as convenience, control, and analytical support, while threats around risk, data privacy, and trust

remain barriers. With the younger, educated demographic leading adoption, there is clear potential for growth in robo-advisory services if platforms can effectively address user threats and build greater trust across broader population segments.

### **RECOMMENDATIONS:**

Based on the analysis and conclusion of the study, the following recommendations are proposed to encourage greater adoption of AI-based financial advisory services among Indian retail investors:

#### **1. Increase Financial and Digital Literacy**

A major factor limiting the use of robo-advisors is limited awareness and understanding of digital financial tools. Financial institutions, fintech companies, and policymakers should invest in financial literacy campaigns, especially targeting underserved demographics such as women, older individuals, and investors from tier-2 and tier-3 cities. Educational initiatives can demystify AI, clarify its advantages, and build confidence among potential users.

#### **2. Build Trust Through Transparency and Regulation**

Perceived threats, such as threats over data privacy, decision-making transparency, and risk of algorithmic failure, deter many investors. To mitigate these fears, robo-advisory platforms should clearly communicate how their algorithms work, what data they use, and how investor risk is managed. In addition, regulatory bodies like SEBI should develop and enforce robust guidelines for AI-based financial services to ensure consumer protection and build long-term trust.

#### **3. Enhance Personalization in Robo-Advisory Services**

Though many investors appreciate autonomy, they still expect personalized advice tailored to their unique goals and risk appetite. Developers should integrate features like customizable portfolios, real-time risk analysis, and scenario-based simulations to make robo-advisors more user-centric and dynamic.

#### **4. Combine Human and Robo-Advisory Models**

A hybrid advisory approach, where human advisors and robo-advisors work in tandem, may help overcome resistance from users who are not ready to fully rely on technology. This model allows users to benefit from AI-driven efficiency while still having access to human judgment, empathy, and reassurance when needed.

#### **5. Target Marketing Towards Young, Educated, and Digitally Active Users**

The study indicates that younger, educated, and financially stable individuals are more open to using AI tools. Fintech firms should focus their marketing strategies on this demographic through digital platforms, social media, and peer influence campaigns. Once early adopters become brand advocates, broader acceptance may follow.

#### **6. Offer Tiered Service Plans**

To encourage adoption among a wider audience, robo-advisory firms can introduce tiered pricing models. A basic free or low-cost version with essential features can attract first-time users, while advanced features and personalized options can be offered in premium versions.

#### **7. Continuous Feedback and User Experience Improvement**

Robo-advisory platforms should incorporate user feedback loops to continuously improve interface design, simplify onboarding, and address customer pain points. User-friendly mobile applications, vernacular language support, and voice-based assistance could enhance accessibility.

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