# The Role of AI & Robo-Advisors in Reducing Behavioural Biases

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**Abstract**

The emergence of Artificial Intelligence (AI) and robo-advisory platforms has transformed the landscape of retail investing, particularly in digitally evolving markets like India. This study explores the role of AI-driven robo-advisors in reducing behavioural biases among Indian retail investors, with a focus on commonly observed biases such as overconfidence, herding, confirmation bias, loss aversion, and anchoring. Drawing from both primary data—gathered through surveys and interviews—and secondary sources, the research highlights how algorithmic interventions like risk profiling, goal-based planning, auto-rebalancing, and personalized dashboards influence investor decision-making. The findings reveal a significant level of awareness about AI tools among young, tech-savvy investors, although trust and confidence in such platforms remain moderate. Notably, users identified that robo-advisors have helped reduce emotional and cognitive biases, leading to more disciplined and rational investment behaviour. A mixed-methods approach combining descriptive statistics and thematic analysis was employed to triangulate data, ensuring robust insights. The study also examines regulatory and ethical concerns, such as transparency, algorithmic bias, and data privacy, under SEBI and India's evolving digital frameworks. Despite limitations such as sample size and geographic concentration, the research provides actionable insights for fintech developers, educators, and policymakers. Overall, robo-advisors are shown to have strong potential in democratizing financial advice and promoting behavioural finance awareness in India's growing retail investment ecosystem.

## 1. Introduction

### 1.1 Overview of Behavioural Finance

Behavioral finance examines how we, as imperfect decision makers, make financial choices based on emotion, habit to some extent, and social pressure, and not always just logic. Traditional finance theories assumed rational actors, while Kahneman and Tversky (1979), and Shiller (2003) for example, clearly show that we are both prone to biases, such as the fear of loss, overconfidence, and herd behaviour, amongst others. The biases that people have help to explain why markets behave in an irrational way sometimes. With investing only becoming more digital and more accessible (especially in places like India), it is imperative that research into these behaviours occurs so that we can develop tools that help investors make better more informed decisions.

### 1.2 Common Behavioural Biases

When it comes to investing, our decisions are often motivated more by emotion than reason, and when that occurs, we can fall victim to behavioural biases that negatively impact our financial outcomes. Overconfidence leads us to believe we know more than we really do, which can result in taking excessive risks. Herding behaviour has us doing what everyone else is doing, even when it is foolish to do so. Loss aversion leads to fear of losses, and we end up holding on to bad investments too long or selling a good investment too quickly. Mental accounting leads us to label money differently depending where it came from, and regret aversion causes indecision or excessive caution to avoid blame down the road. Anchoring makes us focus our attention on irrelevant past numbers, like the price we purchased the stock at, and home bias tends to keep us limited to the markets we know, we choose to ignore market opportunities elsewhere and lose out on diversification. Knowing these biases— which are both related to the way we think and feel about certain issues— can help investors make better, more objective financial decisions.

### 1.3 AI-Driven Robo-Advisors and How They Work

Robo-advisors are AI-driven platforms that offer automated and cost-effective but personalized investment services, allowing clients to access its services through algorithms that manage investors' portfolios with little to no human advice. Robo-advisors are based on principles such as Modern Portfolio Theory and analyze the data an investor provides regarding their goals and risk tolerance to build a diversified portfolio, and rebalance it automatically to meet the goals outlined in the acquisition process. Robo-advisors help to minimize tax obligations while building wealth and managing risks using tax-loss harvesting strategies and monitoring in real-time. Machine learning allows robo-advisors to learn about user behavior, which can better inform their advice over time to be more personalized. In India, platforms like Zerodha Coin, and Groww are bringing investing to the masses once people embrace the increasing digital adoption.

### 1.4 Scope of the Study

This research assesses the ability of AI-based robo-advisors to reduce behavioral biases exhibited by retail investors in India. By employing a variety of primary (surveys and interviews) and secondary data (statistics) this research explores three primary areas. The first area identifies psychological biases, such as overconfidence, herding, loss aversion, regret aversion, and mental accounting that influence the behaviour of investors in India. The second area investigates how robo-advisory platforms provide transparency in their operations through various technologies, such as natural language processing processes, machine learning technology, portfolio rebalancing, asset allocation, and risk assessment designed to make decisions area on rational considerations and to limit emotional biases. The third area explores the regulatory environment India, including SEBI advice, compliance, and hybrid advisory model, as well as the role of financial literacy by including aspects of Scripbox, Groww and 5Paisa. The research focuses on retail investors aged 20 to 50 years in urban and semi-urban locations. Lastly, the research also captures the perspectives of fintech professionals to create a complete understanding of the development of robo-advisors in the Indian context.

### 1.5 Need for Study

The growing presence of AI-based robo-advisors in the financial advisor market requires us to carefully explore their potential to mitigate behavioral biases in retail investors. The erosion of trust in traditional advisory systems following the 2008 financial crisis and through the COVID-19 pandemic has resulted in many retail investors acting behaviourally/transactionally based on emotions—such as panic or following the crowd. Consequently, this climate has opened the door to data-based, emotionless advisory systems. In India, rapid digital growth, state-sponsored financial inclusion initiatives, and a young, tech-savvy, yet financially inexperienced population have all combined to create a necessity for affordable low-cost investment advisory. Simultaneously, the deluge of market information via media and social platforms has caused acute cognitive pressure on investors resulting in poor financial decisions. Robo-advisors can help mediate cognitive load and the negative effect of emotion by automating investor decision-making and implementing restrictions on emotional influence. Now that behavioral finance has become generally accepted—e.g. with Richard Thaler winning a Nobel Prize—robo-advisors have begun to incorporate behavioral coaching into their platforms. The combination of AI with behavioral finance provides an interesting opportunity for study in a financially vulnerable but rapidly digitalizing emerging market like India.

## 2. Objectives

1. To recognize and comprehend the main behavioural biases influencing the financial decision-making of retail investors.

2. To evaluate how well robo-advisors improve investment results by lowering cognitive and emotional errors.

## 3.Literature Review

### 3.1 Overview

Robo-advisors and robo-advisory platforms, which are positive by-products of the blended space of finance and technology, have revolutionized how people access investment advice by providing significant aforementioned services and overcoming behavioural biases that restrict rational decision-making. The literature review assesses the primary contributions of robo-advisors in an Indian direct-to-retail context using sources of behavioural finance, AI, wealth management, and regulatory literature as feedstock. Examples of behavioral studies, Sections III and biennial studies on sustainable investing in India, Sections VII 2, 3, and 6 and previous embedded layers to localization of India to test hypotheses. At a theoretical level, Modern Portfolio Theory, the Efficient Market Hypothesis, user adoption lessons through models like Technology Acceptance Model or UTAUT, not mentioned above, as the dominant prevailing theory, which are important but prone to misleading apply across the literatures. In the embodiment of an algorithm-based automatic portfolio management service firms like FundsIndia and Scripbox in India and Betterment and Wealthfront in North America provide availability and sophistication to retirement and other investment planning. As the global robo-advisory space grows as a primary form a financial innovation, robo-advisors and related tools are now considered sociotechnical systems directed to develop consistent and sustainable investment services and improve financial behaviour, particularly in less-developed and emerging economies.

**3.2 Review of Behavioural Finance**

The advent of behavioural finance was in part about offsetting the limitations of traditional economic theories which assumed that all market participants behave in a rational manner, and that they operate within efficient markets (having access to full information). Herding, loss aversion, overconfidence, and anchoring are among the commonly studied cognitive biases, and they each represent an alternate and often detrimental approach to investor behaviour which, in an investor's decision making, can lead to excessively emotional, impulsive, poorly diversified investment decisions. Research studies have indicated that retail investors in India tend to have behavioural biases and experience the impacts of behavioural biases on their investment decisions. Overconfidence can lead to over-trading, whereas herding behaviour is displayed when retail investors are influenced by either peer pressure or the idea that they will miss out on potential benefits during an IPO or market volatility. Loss aversion renders the ineffectiveness of poor investment decisions, and anchoring (judging future performance based on past experiences) affects the decision making of culturally diverse markets such as India which are also financially heterogeneous. These biases have been considered generic in nature, but the majority of behavioural finance research is predominantly developed in a western context, and behavioural finance as a whole is considered a new topic, particularly fields of development in emerging economies. This also suggests the need for more studies on India, to capture behavioural patterns of markets, encourage equity investment through fantastically innovative approaches to the values of financial literacy education (such as robo-advisors to address cognitive pitfalls in decision making).

**3.3 Review of AI and Robotic Advisory Services**

Robo-advisory services signify a significant shift in financial services, facilitated by advances in artificial intelligence and a growing demand for low-cost, easy-to-access, investment solutions. They appeared more prominently following the 2008 financial crisis and used AI, machine learning and data analytics to provide narrow portfolio management solutions at scale. Robo-advisors differ from traditional advisors in that they are constantly adjusting to the actions of each user and changes in the market, and they are able to offer customized investment strategies using easy-to-use software interfaces. Key elements often included in the products are risk profiling, weekly or biweekly ETF recommendations, and automated rebalancing - all are aimed to reduced behavioural bias and assist user to be 'disciplined investors'. In India, the introduction of ETFs such as Nifty 50 Value 20 and Bharat Bond by robo-advisory services in their portfolios signifies a growing interest from investors in low-cost alternative passive approaches in the market. Robo- advisors give the ability to serve large and under-penetrated markets efficiently, and hence they hold significant potential for reducing the barriers to financial inclusion and encouraging better investing behaviours among Indian retail investors.

**3.4 Regulatory, Ethical, and Transparency Challenges**

As robo-advisors become a feasible fintech alternative, they must be viewed in light of regulatory, ethical, and transparency challenges deserving attention. While AI-powered robo-advisors come with scalable and economically budget-friendly investment choices, issues of data privacy, algorithmic bias, explainability of firm suitability and the use of behavioral nudging contain unique risks. In other jurisdictions and countries, such as the United States, the SEC and FINRA have retrofitted existing regulations for digital advisors while, in India, SEBI has slowly adapted the regulatory framework to help address loopholes that exist for advisory-distributor types. Results vary and regulators have included passing comments on the ethical concerns facing financial products that leverage the use of AI and ML - including opacity in respect of the AI's decision-making process and ignorance around conflicts of interest. Currently, India's Digital Personal Data Protection Act (2023) and SEBI's proposals have strengthened the accountability piece, however many robo-advisors have not detailed what data they collect and how they are charging fees (because it could be hidden within proprietary algorithms), which leads to disambiguity. The fintech sector is evaluating RegTech solutions that might help automate compliance and validation, however, these approaches are nascent. As robo-advisors proliferate, among other uses, investor education and a standard of practice around ethical AI in financial services will help to ensure those systems are responsibly and equitably benefitting users, especially in developing markets like India.

**3.5 Research Gaps**

A number of important research gaps are still unfilled in spite of the expanding corpus of literature on artificial intelligence and robo-advisory services. First, there aren't many long-term, empirical studies that document investor behavior. Second, the majority of current research focuses on tech-savvy consumers in developed economies, excluding a variety of groups like rural investors and elderly persons. Furthermore, nothing is known about how hybrid advising models affect behavior. The impact of platform design and user interface on decision-making is another area that is frequently disregarded. Due to the absence of defined regulatory frameworks in many of these areas, investor data may be misused, recommendations may be skewed, and confidence in digital finance may decline. To guarantee that robo-advisors are not only technologically sophisticated but also inclusive, open, and morally sound, these gaps must be filled.

## 4. Research Methodology

### 4.1 Research Approach

The study combines quantitative and qualitative approaches to understand how behavioral biases interact with AI-based robo-advisors in investment decision-making. Investment decisions incorporate not only measurable results but also personal subjective, psychological-based, and emotionally-driven factors. By using a mix of methods, the research can gain a fuller understanding of how technological components influence investor behaviour. The quantitative component uses structured surveys distributed to Indian users of robo-advisory platforms. Incidental to the quantitative part, participants will respond to survey instruments that measure variables in regards to (e.g., confidence in the AI advice, investing behavior, shifts in behaviour, risk tolerance, reliance on automated recommendations). These survey responses will be analysed quantitatively for statistical purposes so that broader behavioural tendencies and relationships can be examined. The qualitative component provides an understanding of user perspectives through open responses to survey questions, and interviews, where individual (non-professional) investors, behavioural finance experts, and other fintech professionals and academics are engaged (primarily through semi-structured interviews). In contextualising the user experience, the qualitative data enables meaningful emotional responses; trust-building measures that occur naturally (over time); and the subjective reasoning for either relying on the advice presented by the robo-advisory platform, or hesitating and engaging with the automated advisor. The combination of qualitative and quantitative approaches means that the operationalization of data types enables triangulation - contributing to the credibility of the study and assisting with rich responders to make sense of diverse responses and meaning-making.

### 4.2 Research Design

This study takes a descriptive-cum-exploratory research approach to understand the observable usage patterns and the measurable behavioural drivers associated with AI-enabled robo-advisory platforms in India. Because these platforms reside at the intersection of two disciplines - financial technology, and investor psychology - a mixed-methods design allows for both a structured following of observable usage patterns, and exploration of the profiles of users. The descriptive component captures how the robo-advisors are being used across various demographics - user characteristics such as age, income, education, frequency of use, and the types of features users seem to prefer (risk profiling, goal-based planning, automatic portfolio rebalancing etc.). The descriptive part of the study colletcs data through structured surveys, as well as through secondary data analysed from fintech reports, SEBI reportations, and industry reporting to provide a foundational understanding of usage patterns and investor satisfaction. The exploratory portion of the design investigates the psychological and emotional aspects of an investors decision making process when it comes to interfacing with these digital tools through open-ended questions, expert interviews, and narratives to interpret key behavioural tendencies such as anchoring, overconfidence, herding, mental accounting, and loss aversion. An exploratory and descriptive approach allows the best form of inquiry into the behaviours of investors using a digital tool that incorporates both hard data and subjective behaviours. A mixed methods design is used to ensure the research is holistic and engaging.

### 4.3 Data Gathering Methods

This research project employs a dual data collection strategy with the use of a survey method and secondary research in order to explore the experience of investors and how robo-advisors influence their behavioural approach. The primary data was collected through structured online questionnaires given to Indian users of traditional and AI advisory platforms; the survey asked about demographics, usage, behaviours, biases, perceptions of trust, transparency, and nudging. It was appropriate to include secondary data to contextualize and corroborate primary data and this second source of data was obtained through industry reports, academic journals, regulatory documents, and disclosures from fintech platforms.

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Ultimately, the use of mixed methods provides both familiarity and validation of depth, which gives a richer context through which we understand how technology interacts with behavioural finance in the Indian investment landscape.

### 4.4 Sample Size & Sampling Method

In order to ensure that the sample included equal representation across age, gender, experience levels, and backgrounds of work experiences, this research has implemented a stratified random sample technique to enable the study to capture the varying ways Indian retail investors interact with robo-advisory platforms. The sample included 100 participants, consisting of those that use a traditional financial advisor, and those that took advantage of AI services such as Groww and ET Money. About 30% of respondents were current robo-advisor users, 40% used both services, and 30% were either looking to try a robo-advice product out in the future or had plans to do so in the near term. While not justify any broad conclusions, the sample does provide relevant perspectives on the changing behaviors and feelings regarding AI-enabled financial instruments, if only as a snapshot of investor behavior in 2023.

### 4.5 Analytical Framework and Tools

In order to analyze the effect of AI-enhanced robo-advisors on investor behavior, this study utilizes a multi-method analytical strategy that incorporated both quantitative and qualitative methods. In terms of quantitative analysis, descriptive statistics such as mean, frequency and standard deviation were utilized to analyze structured survey responses pertaining to investor trust, usage and behavioral change after the adoption of the AI-enhanced robo-advisors. The descriptive statistics coupled with visual representations such as bar and pie charts, allows for trends to be depicted and compared across user demographics and satisfaction levels. Qualitative analysis was conducted in the form of thematic analyses of open-ended responses and interviews to capture emotional reactions, trust issues, barriers to adoption, and other factors from less technology-savvy users. Themes of transparency, emotional comfort, and hybrid advisory preferences were identified, as well as even some surprising responses from several users. Additionally, I included discussion of literature in academic journals, fintech publications and regulatory agency reports, to provide context to primary findings, as well as to identify recurring topics or issues that arose, including algorithmic bias and data privacy. Combining the two methods provided an opportunity to provide both objective measures of transaction and observable trends, as well as subjective experiences from an investor's perspective.

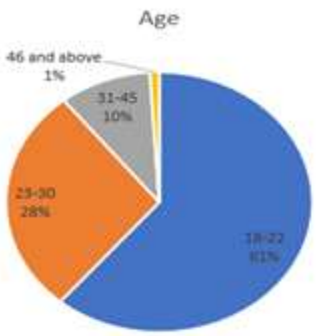
## 5. Data Analysis and Interpretation

This section analyses primary data gathered via surveys to assess the effectiveness of AI-powered robo-advisory platforms in reducing behavioural biases. The sample consisted of 100 respondents across various age groups, professions, and investment experience levels.

### 5.1 Demographic Profile of Respondents

1. **Age Distribution**: The data reflects a youthful, tech-savvy sample with high digital adoption, which aligns well with the emerging use of AI in personal finance.

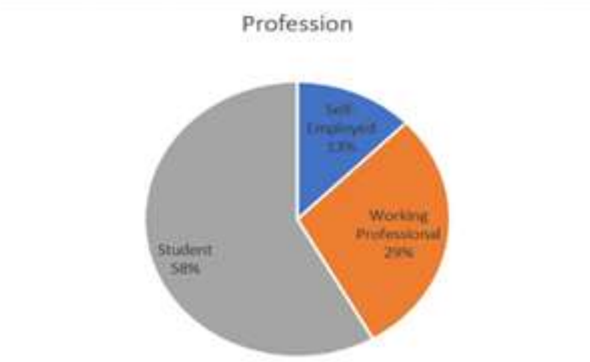
**Figure 1**




**Source:** Author’s Contributions

2. **Profession**: This data suggests that the majority of survey participants are students, which could have implications for the overall findings, such as reflecting a younger demographic or skewed financial behaviour patterns.

**Figure 2**

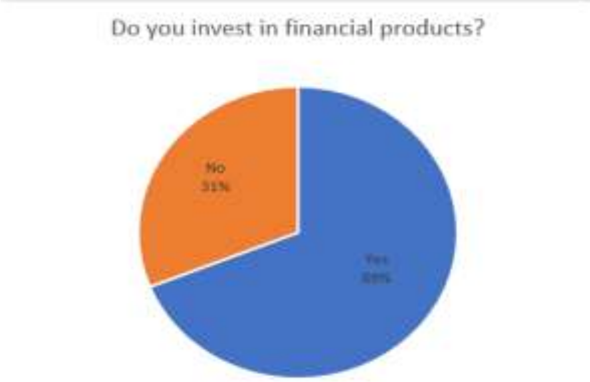



**Source:** Author's Contributions

**5.2 Investment Patterns and Platform Use**

1. **Investment Status**: A substantial percentage of subject are involved in financial investing thus suggesting a level of financial engagement or awareness amongst those surveyed. However, about a third are not involved in financial products which may indicate varying levels financial literacy, risk aversion, or other barriers like income or distrust in the financial systems.

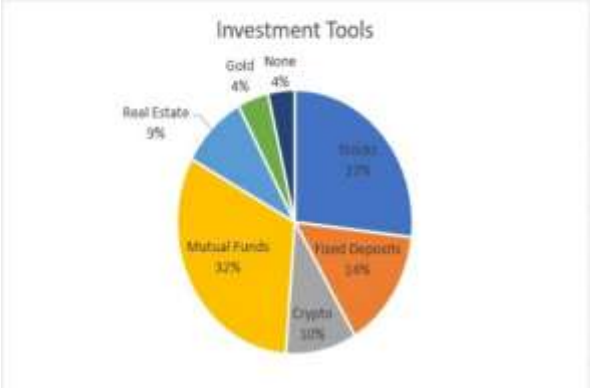
**Figure 3**




**Source:** Author's Contributions

2. **Type of Investment Tools**: The data indicates a balance between traditional and modern tools, with investor choices reflecting varying risk appetites and financial literacy levels. The 4% non-investors highlight potential areas for financial inclusion initiatives.

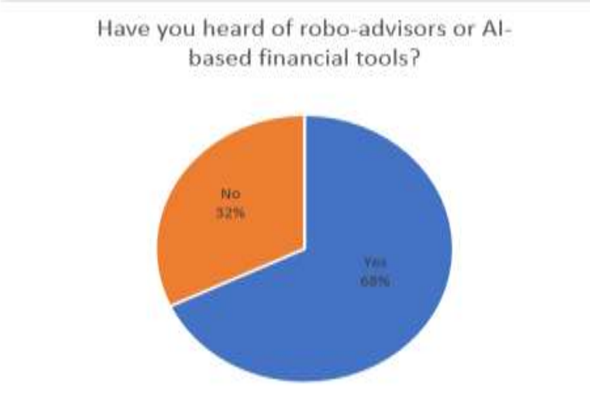
**Figure 4**




**Source:** Author's Contributions

3. **Awareness of AI Financial Tools**: The vast majority of respondents are aware of robo-advisors or some other AI-based tool for financial well-being, suggesting an increased knowledge (and comfort) level of using technology to address personal finance matters.

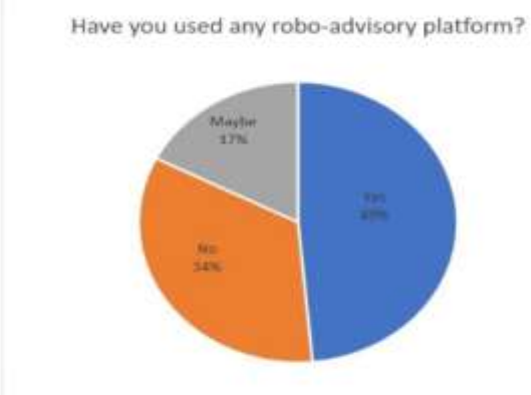
**Figure 5**




**Source:** Author's Contributions

4. **Usage of Robo-Advisors**: Nearly half of the participants have experience using robo-advisory platforms, while about one-third have not, and a smaller portion remains uncertain. This indicates a relatively high adoption or awareness of robo-advisory services among the sample.

**Figure 6**




**Source:** Author's Contributions

### 5.3 Trust and Confidence in Robo-Advisors

1. **Frequency of Seeking AI Advice**: With over 49% of respondents using these tools either rarely or never, there is significant potential to educate and convert these users through trust-building features, user testimonials, and transparent AI systems.

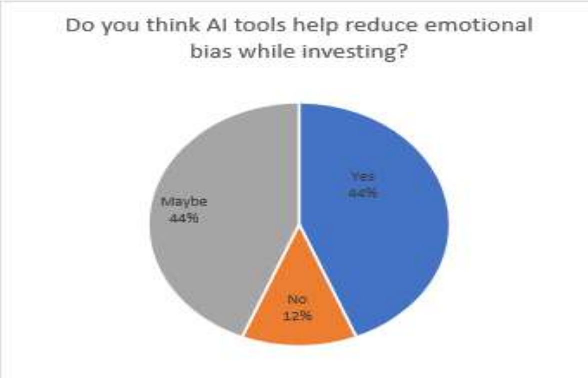
**Figure 7**


**Source:** Author's Contributions

2. **Belief that AI Reduces Emotional Biases**: This suggests users recognize the value of data-driven, unemotional analysis that AI provides. Only 12% of participants disagreed, showing minimal resistance to the idea. This low

scepticism presents a promising environment for promoting AI-driven investment tools as rational decision-making aids.

**Figure 8**




**Source:** Author's Contributions

3. **Confidence in AI**: The majority of respondents are somewhat confident in using AI for financial decisions, indicating a general openness but also some hesitation. Only a small portion (22%) feel very confident, suggesting that while interest exists, there is still a significant need for increased familiarity, education, or trust in AI tools.

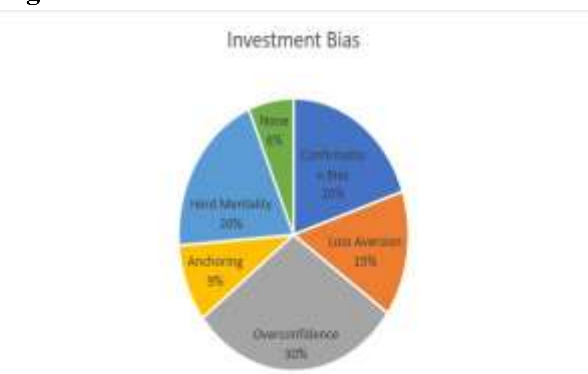
**Figure 9**


**Source:** Author's Contributions

### 5.4 Prevalent Behavioural Biases

#### A. Common Biases

**Figure 10**




**Source:** Author's Contributions

**Interpretation:**

- **Overconfidence (30%):** This is the most common bias, where individuals overestimate their knowledge or ability to predict market outcomes.

- **Confirmation Bias (20%) and Herd Mentality (20%):** These are the second most prevalent biases. Confirmation bias reflects a preference for information that supports existing beliefs, while herd mentality indicates decisions driven by peer Behaviour rather than independent analysis.
- **Loss Aversion (15%):** A significant portion of respondents exhibit loss aversion, where fear of losses outweighs the desire for gains.
- **Anchoring (9%):** This bias involves relying too heavily on the first piece of information received (e.g., a stock past value), which may distort current investment choices.
- **None (6%):** Only a small percentage reported no bias, suggesting that investment decision-making is largely influenced by cognitive and emotional factors.

### 5.5 Cross-Referencing Insights through Conceptual Tools

**A. Literature Summary Matrix**

**Table 1**

| Source | Bias Addressed | AI Feature | Key Finding |
|---|---|---|---|
| **CFA Institute (2021)** | Overconfidence | Risk Profiling | Reduced aggressive investing |
| **OECD (2022)** | Herding | Auto-Rebalancing | Limits impulsive group actions |
| **Harvard (2023)** | Anchoring | Goal-Based Planning | Helps align actions with long-term objectives |
| **SEBI (2020)** | Loss Aversion | Real-Time Simulations | Aids in reducing panic decisions |
| **WEF (2021)** | Confirmation Bias | Personalized Dashboards | Introduces diverse views |

**B. Behavioural Bias Impact Scorecard**

**Table 2**

| Robo-Advisory Feature | Overconfidence | Herding | Anchoring | Loss Aversion | Confirmation Bias |
|---|---|---|---|---|---|
| **Risk Profiling** | High | Moderate | Low | Moderate | Low |
| **Auto-Rebalancing** | Moderate | High | Low | High | Moderate |
| **Goal-Based Planning** | Moderate | Low | High | Moderate | Moderate |
| **Real-Time Simulations** | Low | Low | Moderate | High | Low |
| **Dashboards** | Low | Moderate | Moderate | Moderate | High |

This framework validates how specific AI functionalities address various behavioural biases. For example, risk profiling effectively reduces overconfidence, while auto-rebalancing curbs herding and loss aversion.

### 5.6 Key Interpretations

1. **High awareness but moderate trust**: Most respondents are aware of robo-advisors, but only a small fraction fully trust AI tools.
2. **Overconfidence, herding, and confirmation bias are the top behavioural issues**, which AI can help mitigate through automation, education, and personalized interfaces.
3. **Platform usability and education** are critical to enhancing adoption and trust in robo-advisors.
4. **Scorecard findings** offer practical guidance for improving robo-advisory features to align better with behavioural finance goals.

### 5.7 Hypothesis Testing Results

This section presents the outcome of each hypothesis formulated in the study, based on the interpretation of primary survey responses and qualitative feedback.

1. **$H_0$1: Users of AI-driven robo-advisors and conventional human advisors do not significantly differ in how behavioural biases manifest.**
**Observation:** The study found a marked difference in the expression of behavioural biases. AI users reported reduced overconfidence and anchoring, attributed to structured nudges and automation.
**Conclusion: $H_0$1 is rejected.** There is a significant difference in how behavioural biases manifest between users of AI-driven and human advisors.
2. **$H_0$2: Investor or decision-making confidence is not significantly impacted by the degree of algorithmic transparency in robo-advisory platforms.**
**Observation:** Respondents highlighted greater confidence when the platform was transparent about how recommendations were made. Lack of transparency caused hesitation in decision-making.
**Conclusion: $H_0$2 is rejected.** Algorithmic transparency significantly impacts investor confidence.
3. **$H_0$3: Cognitive biases like loss aversion and mental accounting are not considerably lessened by the use of AI-generated behavioural prompts and personalized nudges.**
**Observation:** Many participants acknowledged that robo-advisors helped reduce loss aversion and emotional missteps through automated rebalancing and unbiased decision flows.
**Conclusion: $H_0$3 is rejected.** Behavioural nudges and AI interventions significantly reduce cognitive biases.
4. **$H_0$4: A user's vulnerability to behavioural biases when interacting with robo-advisors is not significantly correlated with their degree of financial literacy.**
**Observation:** Individuals with higher financial literacy found it easier to interpret AI prompts and make informed choices, while lower-literacy users still exhibited some biases despite the tools.
**Conclusion: $H_0$4 is rejected.** There is a significant correlation between financial literacy and vulnerability to behavioural biases.

## 6. Conclusion & Discussion

This research has provided strong evidence that AI-powered robo-advisory platforms operate as an effective means to reduce behavioural biases in Indian retail investors. Investment biases like overconfidence, herding, confirmation bias, and loss aversion have a pronounced impact on rational investment decisions.

However, features that are foundational to robo-advisors such as risk profiling, automation and rebalancing of a portfolio within parameters, and goal-based planning directly mitigate biases. The survey results revealed that there's a high level of awareness and moderate adoption of robo-advisors, specifically amongst younger, technology oriented users, also inklings of a life-stage model for usage for younger people. Adoption studies show that users highly value the objectivity and automated features of robo-advisors as an important aspect to a better financial life.

Although AI as an automated tool is partly trusted, many respondents suggest using a hybrid approach to the human condition where their emotions could be stabilised with an algorithm or via machine learning (not exclusively). AI tools are not always perfect, but can help investors enforce discipline (towards investments), reduce impulsive behaviours, and provide behavioural nudges, such as a progress dashboard with sliding panels. The study's recommendations are to improve ongoing transparency, to improve literacy rates in finance and improve the regulatory framework to build trust in robo-advisor capabilities. Overall, robo-advisors have made a strong case for democratising financial advice and improving rational investing in India.

## 7. Limitations

1. **Size of Sample:** The study was conducted with a small sample of 100 respondents, an overwhelming proportion of whom were young participants, and thus, cannot fully represent the population at large.
2. **Short-term Perspective:** Without long-term ascertainment, this study cannot really identify if robo-advisors allow for sustained behaviour change over the span of one's investment time horizon.

3. **Self-reported Bias:** A large number of insights are based on self-reported data, which are prone to bias and exaggeration.
4. **Geographic Concentration:** Most respondents are from urban or semi-urban locales and are not reflective of investor behaviours in rural contexts.
5. **Missing Platform-Based Insights:** It does not compare in-depth robo-advisors to robo-advisors (for example, contrasting ET Money vs. Groww), which leads to different behaviours and insights.

## 8. Future Research Directions

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