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AUTOMATING RATIONALITY: THE POTENTIAL OF ROBO-ADVISORS IN REDUCING BEHAVIORAL BIASES

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Abstract
Decision-making in investments is often flawed due to behavioral biases, leading to suboptimal choices. Robo-advisors aim to mitigate these biases through personalized risk assessment. However, their effectiveness in India is understudied. A study of 192 retail investors in Kolkata found that biases like overconfidence and loss aversion lead to irrational investment decisions. Surprisingly, Indian robo-advisors struggle to address these biases. The study suggests that next-gen robo-advisors, informed by behavioral finance insights, are needed to support rational investment decisions. It also highlights robo-advisors' potential to democratize financial guidance, especially for underserved populations, and advocates for greater awareness and adoption in India's financial ecosystem.
Keywords: Individual Decision Making, Behavioral bias, Overconfidence bias, Herding Behavior, Loss aversion bias, Indian Stock Market, Individual investors

1. INTRODUCTION:

Traditional finance theories portray individuals as rational investors (Baker and Filbeck, 2013), evaluating all available information before making investment decisions. However, a growing body of research debunks this notion, revealing that investors often march to the beat of their own drum, swayed by irrational tendencies (Barber and Odean, 2008). Barber and Odean (2001) underscore the impact of behavioral biases on financial decisions, particularly in the context of individual stock selection. Studies repeatedly show that investors, more often than not, make poor investment choices, resulting in lackluster portfolio performance. Behavioral finance steps in to highlight those psychological quirks and emotional reactions lead investors astray from rational behavior (Yoong and Ferreira, 2013). Pompian (2012) aptly describes behavioral biases as mental pitfalls that steer investors toward imprudent decisions. These biases manifest in various ways: overconfidence, where investors overrate their forecasts; the disposition effect, which sees them clinging to losing stocks while selling winners; risk aversion, driving an aversion to uncertainty; and herding, where they blindly follow the crowd (Hoffmann et al., 2010). Research also broadens the lens, exploring investor behavior beyond biases. For instance, Hoffmann et al. (2010) found that investors using fundamental analysis tend to exhibit overconfidence, frequent trading, and higher risk tolerance. Lin (2011) argued that a lack of technical expertise exacerbates biases, while informed decisions hinge on an investor's capability. Interestingly, Nicolosi et al. (2009) observed that despite their irrational behavior, investors do learn from their experiences, suggesting a silver lining to their missteps. Education emerges as a game-changer in tackling behavioral biases (Pompian and Wood, 2006), and Pompian (2012) recommends effective strategies to manage these biases. Ultimately, the extent to which behavioral biases influence investment decisions may hinge on an individual's education level, making financial literacy a key lever for fostering sound investment practices.

The growing buzz in the financial domain suggests that robo-advisory services are stealing the limelight in decision-making processes. In today's breakneck digital era, where automation reigns supreme—spanning net banking, digital payments, e-commerce, and ride-hailing services (Singh and Kaur, 2017)—the integration of automation into everyday life is no longer optional but inevitable. The financial sector is no exception, as automation sinks its teeth deeper into the realm of financial decision-making (Abraham et al., 2019). Robo-advisory services have emerged as cutting-edge platforms offering online investment advice and comprehensive portfolio management (Fein, 2015). Powered by data-driven algorithms, these systems rely on investor inputs through structured questionnaires to build a robust risk profile. This process, aptly termed risk profiling, aims to decode an investor's financial goals, current situation, risk tolerance, and appetite for market uncertainties (Nevins, 2004). As the bedrock of robo-advisory services, risk profiling sets the stage for identifying tailored investment avenues amidst a sea of market options. The magic lies in the tech—AI, big data analytics, social media insights, and psychometric tools can elevate the efficiency of risk profiling to new heights (Tertilt and Scholz, 2018). By harnessing these innovations, robo-advisors can fine-tune their recommendations, steering investors clear of pitfalls like decision inertia (Jung et al., 2018). Moreover, AI has the muscle to shift the needle on behavioral biases, subtly yet significantly mitigating issues like the disposition effect and excessive trading frequency (D'Hondt et al., 2019). In the grand scheme of things, robo-advisors are not just a cog in the automation wheel—they are a game-changer, reengineering how financial decisions are made in a tech-driven world.

The robo-advisory industry is still wet behind the ears, particularly in developing markets like India. Globally, the segment managed an impressive USD 980,541 million in Assets Under Management (AUM) as of 2019, with an average AUM per user pegged at USD 21,421 (Statistics, Market Report, 2019). Despite these promising figures, robo-advisors—a breed of financial advisors that operate with little to no human touch—raise a few red flags for investors (Phoon and Koh, 2017). One key sticking point is the lack of human interaction, which can leave investors high and dry during turbulent times, such as a bearish market. During such periods, many investors value the ability to sit down with a trusted advisor to unpack their emotional and behavioral concerns regarding their portfolios. Without this safety net, they may feel like they're flying blind, leading to insecurity and susceptibility to biases during moments of distress. Behavioral biases, which act as the Achilles' heel of investor psychology, can cloud judgment and pave the way for poor decision-making. Without the human touch to anchor their emotions and provide guidance, investors may find themselves at the mercy of these mental pitfalls, potentially derailing their financial journeys.

The growing treasure trove of insights from behavioral economics and related fields is helping robo-advisory services sharpen their edge in decision-making and refine investor behavior (Silva, 2019; Lam, 2016). With their knack for providing low-cost, passive market access, robo-advisors are proving to be a game-changer. Unlike traditional advisory models reliant on fund managers, robo-advisors have the potential to trim the fat on behavioral biases, offering a fresh take on tackling these psychological pitfalls (Uhl and Rohner, 2018). For investors wary of potential conflicts of interest with human advisors, robo-advisors are the knight in shining armor, delivering impartial guidance with zero emotional baggage (Brenner and Meyll, 2019). Moreover, an advisor's credibility often acts as the linchpin, influencing how much weight investors place on their recommendations (Nikiforova, 2017). In the world of financial advice, where trust is the currency, robo-advisors are carving out a niche as a reliable and unbiased alternative.

A wealth of research sheds light on the growth, adoption, challenges, and evolution of robo-advisory services in developed economies. However, when it comes to the Indian landscape, the literature is as scarce as hen's teeth. Existing studies primarily lean on quantitative approaches to unpack the dynamics and usage of robo-advisory platforms, focusing on their potential to counteract behavioral biases in the Indian context. This research paper sets out to delve into the perspectives of Indian investors who rely on robo-advisory services for their investment decisions. Additionally, it seeks to evaluate the moderating role these platforms play in shaping the investment behaviors of individual investors. By peeling back the layers, this study aims to fill a critical gap in the understanding of robo-advisors' impact in India's unique financial ecosystem.

The spotlight has turned to some fundamental objectives concerning behavioral biases and robo-advisory services, which researchers deem ripe for investigation:

Objective 1: To examine the influence of behavioral biases on investment decision-making among Indian investors.

Objective 2: To evaluate how robo-advisory services act as a buffer, moderating the relationship between behavioral biases and investment decisions.

This study dives deep into the ripple effects of behavioral biases on individual investors in India while unpacking the role of robo-advisors in curbing these biases to elevate the quality of advisory services. Notably, the existing literature comes up short when it comes to empirical insights on the awareness and adoption of robo-advisory services. Given the rapid strides in technology, the evolving perspectives of investors and experts underscore the need for further exploration—not just to understand but to fine-tune and innovate robo-advisory platforms. Hence, the aim of this paper is to investigate the awareness and effectiveness of robo-advisory services in tackling behavioral biases from the standpoint of industry experts, with a view to optimizing these cutting-edge platforms.

2. THEORETICAL BACKGROUND

The interplay between robo-advisory services, behavioral biases, and their impact on investment decisions has flown under the radar in much of the existing research. Behavioral biases—manifesting as overconfidence, risk aversion, and the herding effect—have only scratched the surface in previous studies. While the literature touches on these topics, the treatment has often been cursory, leaving plenty of room for deeper dives and robust discussions. This study aims to fill those gaps by bringing these critical aspects into sharper focus.

2.1 Behavioral Finance:

Behavioral finance, the fusion of psychology and finance (Hirshleifer, 2015), offers a fresh lens to examine investor behavior and the root causes of market anomalies. It veers away from traditional finance theory by shedding light on phenomena like stock market bubbles, and the overreaction or underreaction to new information (Cooper et al., 2001; Zhou and Sornette, 2006). Building on these insights, researchers have further unraveled the pivotal role of psychological factors, distinguishing them from other elements within the framework of behavioral finance. In practice, subjective judgments often drive forecasts from time series data, with their accuracy hinging on the forecaster's ability to anticipate potential directional shifts (Reimers and Harvey, 2011). Historically, finance studies have exposed the magnitude of errors in real-world forecasts but hit a wall when it comes to dissecting the intricacies of time series data that make such predictions challenging (Speekenbrink et al., 2012). These blind spots continue to shape the ongoing quest to refine behavioral finance frameworks and deepen our understanding of investor behavior.

Traditional finance theories have long operated on the assumption that investors behave rationally (Rizvi and Fatima, 2015). However, events like the 2008 financial crisis and its ensuing market crash served as a wake-up call, exposing the cracks in this presumption. These irrational behaviors have paved the way for behavioral finance to take center stage as the go-to framework for understanding such anomalies. Behavioral finance unpacks investor behaviors by blending real-life influences with specific psychological factors, such as overconfidence, representativeness (Tekce and Yılmaz, 2015), and herding behavior (Chiang et al., 2010). To bridge the gaps left by traditional rational models, researchers have developed behavioral financial models that integrate psychological and sociological dimensions, offering a more nuanced explanation for market anomalies and investor actions (Muradoglu and Harvey, 2012). This study extends the reach of behavioral finance by examining how AI-driven robo-advisors factor investor behavior into portfolio selection strategies. By addressing the role of behavioral biases—categorized into optimism and pessimism—it sheds light on their impact on investment decisions. Specifically, two sentiment dimensions are analyzed: loss-aversion and overconfidence. Additionally, given humanity's innate tendency to follow the crowd, herd behavior is also scrutinized. This comprehensive approach aims to decode the psyche behind investor choices and refine portfolio strategies accordingly.

2.2 Behavioral Bias and Investment Decision

2.2.1 Overconfidence

Overconfidence stems from various situations of overestimation, where individuals become overly sure of their knowledge and abilities. These bias rears its head when investors inflate their predictions to an extreme degree (Budiarto, 2017). Overconfidence in individual investors can significantly sway their investment decisions (Pradikasari and Isbanah, 2018). According to Kartini and Nahda (2021), this bias casts a significant shadow, leading to negative consequences in decision-making. Interestingly, Jain et al. (2023) find that women investors tend to exhibit lower levels of overconfidence and are generally more risk-averse than their male counterparts. In addition, men tend to trade more frequently, but their returns are often lower. Agha and Pramatheran (2023) add another layer, suggesting that overconfident traders can outperform purely rational traders when it comes to capitalizing on mispricing caused by liquidity issues or noise traders. This nuanced view of overconfidence reveals how biases can both hinder and, in some cases, enhance trading strategies depending on the market conditions.

H_1. Overconfidence bias impacts investment decision of investors.

2.1.2 Risk-aversion

The loss-aversion bias, a cornerstone of prospect theory (Kahneman and Tversky, 1979), explores how individuals react more strongly to potential losses than to equivalent gains. Roth and Voskort (2014) highlight those female investors typically exhibit risk-averse behavior, while male investors tend to take on more risk. Statman (2010) points out that professional portfolio managers are generally more cautious, displaying a lower risk appetite when making investment decisions. Research by Ningram et al. (2023) delves into the cause-and-effect relationship between risk perception and investment choices. Previous studies consistently show that women are more risk-averse than men (Morgenroth et al., 2023; Dawson, 2023). However, Pinjisakikool (2017) finds that there is no clear link between the level of risk aversion measured and actual behavior, suggesting that attitudes don't always match actions. Barberis et al. (2001) examined loss aversion within a consumption-based model, using prospect theory to assess how financial assets are valued. Yechiam (2019) further illustrates that the degree of loss aversion largely hinges on past experiences, particularly when comparing gains and losses. This research underscores the complex and nuanced nature of loss aversion in investment decision-making.

H_2: Risk-aversion bias impacts investment decision of investors.

2.2.3 Herding

Herd mentality refers to the phenomenon where typically rational investors start making decisions based on the actions and evaluations of others, rather than their own independent analysis (Malik & Elahi, 2014). Instead of relying on personal judgment, investors often lean on firsthand information from their reference groups to guide their decisions (Robin & Angelina, 2020). In this environment, investors focus on the collective wisdom of the crowd to shape their choices. Rahman et al. (2020) highlight that investor with low confidence are more likely to follow the advice of others, while Herlina et al. (2020) explored herd behavior within institutional investors. Studies across various global stock markets provide compelling evidence of herd mentality, including the Indonesian stock market (Rahayu et al., 2021), the Pakistani stock market (Javaira and Hassan, 2015), the Sri Lankan stock market (Kengatharan and Kengatharan, 2014), and the Indian stock market (Kanojia et al., 2022). Interestingly, Gupta and Goyal (2024) found that male and female investors in India exhibit similar herding behavior, challenging prior research that suggests gender differences in the way individuals respond to the herd mentality. This research throws a wrench in the commonly accepted narrative, calling for a reevaluation of how herding behavior manifests across genders.

H_3: Herding bias impacts investment decision of investors.

2.3 Moderating Role of Robo Advisory: (Samugathan2020)

By automating tasks like portfolio rebalancing and delivering personalized recommendations, robo-advisors help investors stay on track, especially during turbulent market conditions, allowing them to focus on their long-term financial objectives (Echiler and Schwab, 2024). Many of these platforms also feature educational tools that boost financial literacy, bridging knowledge gaps and empowering users to make more informed, rational decisions. Additionally, the inclusion of nudges—such as goal tracking and progress monitoring—reinforces positive financial behavior. As a result, robo-advisory systems can significantly enhance investment outcomes and overall financial health, serving as an effective remedy for behavioral pitfalls in finance (Shanmuganathan, 2020). However, the extent to which robo-advisors mitigate the effects of behavioral biases—such as overconfidence, loss aversion, and herding behavior—remains underexplored, which is the crux of this study. With that in mind, the following hypothesis has been put forward.

H_4: Robo-advisory service moderates the relationship between OC and ID
H_5: Robo-advisory service moderates the relationship between RA and ID
H_6: Robo-advisory service moderates the relationship between HERD and ID

2.4. Research Model

Proposed research model for the present study is shown herewith.

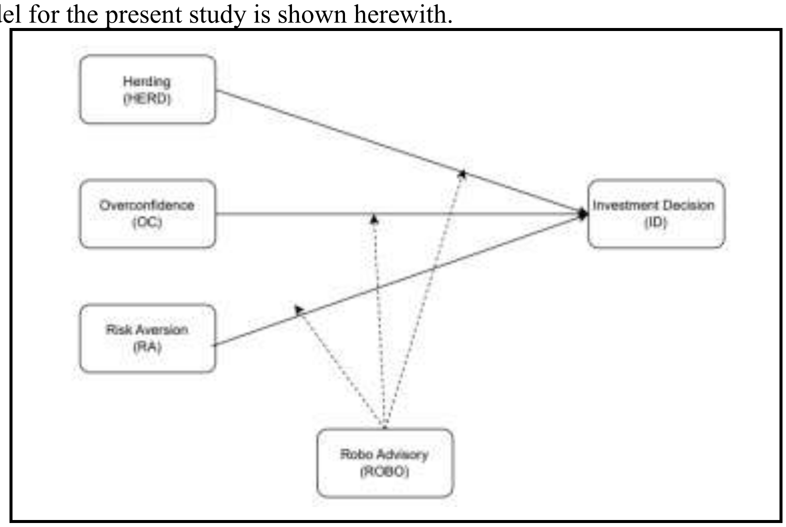

Figure 1: Proposed Measurement Model

3. METHODOLOGY

This section is divided into three subsections. Subsection 1 delves into the constructs employed to assess personality traits, risk-taking attitudes, and cognitive biases. Subsection 2 outlines the data collection process and presents key characteristics of the sample. Lastly, Subsection 3 focuses on the methods used to evaluate the reliability and validity of the data.

3.1 Research Constructs

The scales used to measure risk aversion, herding behavior, and overconfidence bias were adapted from the frameworks outlined by Quasim et al. (2019) and Nofsinger et al. (2018), while the scale for robo-advisory services was drawn from Todd and Seay (2020). Each item was assessed using a five-point Likert scale, ranging from "strongly disagree" to "strongly agree."

3.2 Data Collection

The data was gathered via an electronic survey from Indian investors who rely on robo-advisory systems for their investment decisions. A total of 207 investors took part in the survey, with 192 valid questionnaires included in the analysis. Fifteen responses were discarded due to incomplete information.

4. RESULTS AND ANALYSIS

This section is broken down into three subsections. Subsection 1 outlines the key characteristics of the sample. Subsection 2 explains the measurement model employed to validate and ensure the reliability of the constructs. The final subsection offers a comprehensive analysis of the empirical findings.

4.1 Demographic Analysis

Table 1: Demographic Profile of Respondents

		Frequency	**Percentage**
Gender	Male	107	56%
	Female	85	44%
Age	21-30	64	33%
	31-40	95	49%
	41-50	31	16%
	Above 51	2	1%
Total		**192**	**100%**

In the current study, 56% of the respondents were male, while 44% were female investors. The results indicate that male respondents were more active in participating than their female counterparts, likely because a higher proportion of men are involved in stock market investments. The table above shows that 33% of the sample falls within the 21 to 30 age group. Meanwhile, 49% of the respondents are between 31 and 40 years old, and 16% are between 41 and 50. Only two respondents, both over the age of 51, participated in the study. Overall, the sample is predominantly composed of individuals in the 31 to 40 age range.

4.2 Measurement Model Analysis

The below figure shows the results of Confirmatory Factor Analysis by using Smart PLS 4 software.

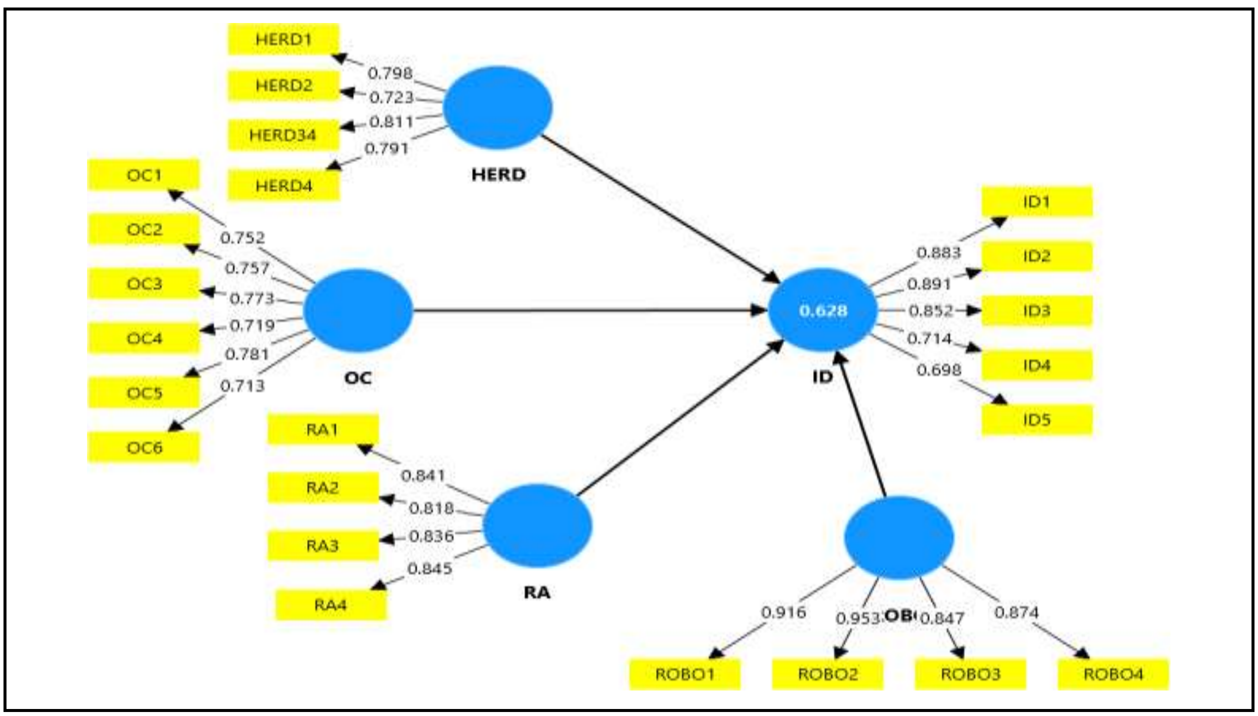

Figure 2: Measurement Model for CFA

The figure above shows the loading of each item, generated using SmartPLS software. According to standard practice, item loadings should exceed 0.60 (Hair et al., 2017). In line with this, we adopted the >0.60 threshold, as recommended by researchers in the social sciences. The results indicate that all items meet or surpass this recommended loading value.

In SmartPLS analysis, composite reliability is favored over Cronbach's α, with values above 0.70 signifying reliability, and values above 0.90 potentially indicating multicollinearity (Hair et al., 2017). To assess convergent validity, this study employed Average Variance Extracted (AVE), with values exceeding 0.50 reflecting strong support. The table below presents the Cronbach's α, composite reliability, and AVE scores, highlighting the internal consistency and convergent validity of the reflective constructs.

Table 2: Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
HERD	0.789	0.796	0.862	0.611
ID	0.867	0.875	0.905	0.659
OC	0.844	0.846	0.885	0.562
RA	0.858	0.868	0.902	0.698
ROBO	0.920	0.929	0.944	0.807

4.3 Regression Analysis

Once the measurement model is validated, the Smart PLS analysis assesses the significance of the paths, the effect size using f^2, the relevance of endogenous constructs through R^2 and Q^2, and tests the hypotheses of the study.

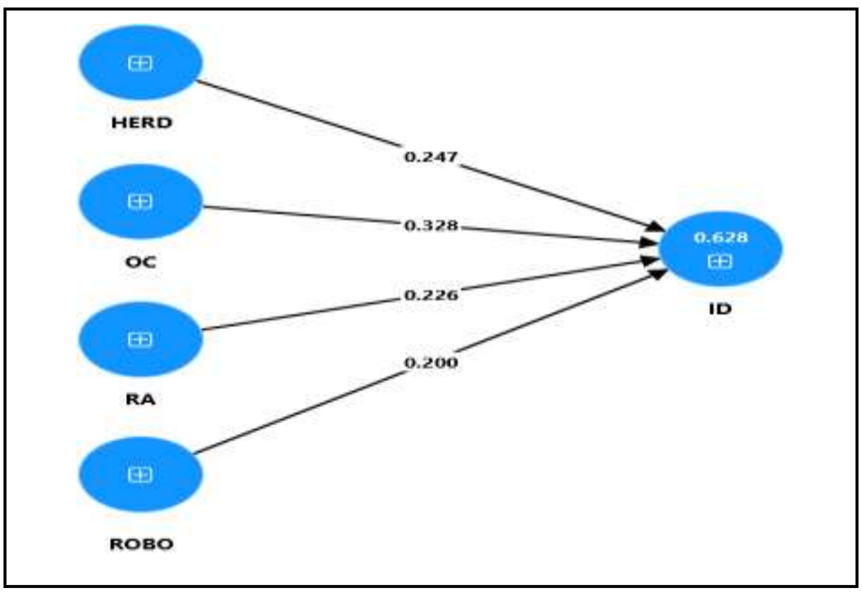

Figure 3: Regression Analysis

Upon analyzing the VIF values for the path model, it was found that all values were below the threshold of 5, indicating the absence of collinearity among the variables. The results are presented in the table above.

In the SmartPLS analysis, path model coefficients (β) were evaluated to assess the hypothesized relationships between the variables. These coefficients can range from -1 to 1, as outlined by Hair et al. (2017). Effect sizes (f^2) were calculated to determine the influence of exogenous constructs on endogenous constructs in the structural model. Cohen (1992) provided guidelines for interpreting f^2 values: values below 0.02 indicate no effect, between 0.02 and 0.15 suggest a small effect, from 0.15 to 0.35 indicate a medium effect, and values of 0.35 or higher signify a large effect. These f^2 values, along with two-tailed t-values and corresponding p-values, are presented in the table.

The table below presents the path model coefficients (β), two-tailed t-values, effect sizes (f^2), and corresponding p-values used to estimate the relationships between dependent and independent variables. The path model coefficients represent the change in the dependent variable in standard deviations for each standard deviation change in the independent variable (Hair et al., 2017).

Table 3: Hypothesis Testing

Hypothesis	Beta Value	f-square	t-value	P values	Decision

H_1: OC -> ID	0.395	0.258	5.767	0.000	Accepted
H_2: RA -> ID	0.281	0.129	4.586	0.000	Accepted
H_3: HERD -> ID	0.271	0.128	4.317	0.000	Accepted

The table above displays the beta, f², t-statistics, p-values, and corresponding decisions for each relationship. The results indicate that only representative bias has an insignificant impact on investment decisions, leading to the acceptance of all hypotheses except H5.

Table 4: R-square

	Investment Decision (ID)
R-square	0.603
R-square adjusted	0.595

The findings of this study reveal that the path model shows a statistically significant but moderate coefficient of determination (R^2) for the endogenous variable, investment decision (0.414). Additionally, the Q^2 scores indicate a moderate level of predictability, with a value of 0.419.

4.4 Moderation Analysis

In this study, the model tested the moderating variables (robo-advisory) over independent variables (Herding behaviour, Over-confidence Bias, Risk Aversion Bias) and dependent variable (Investment Decision).

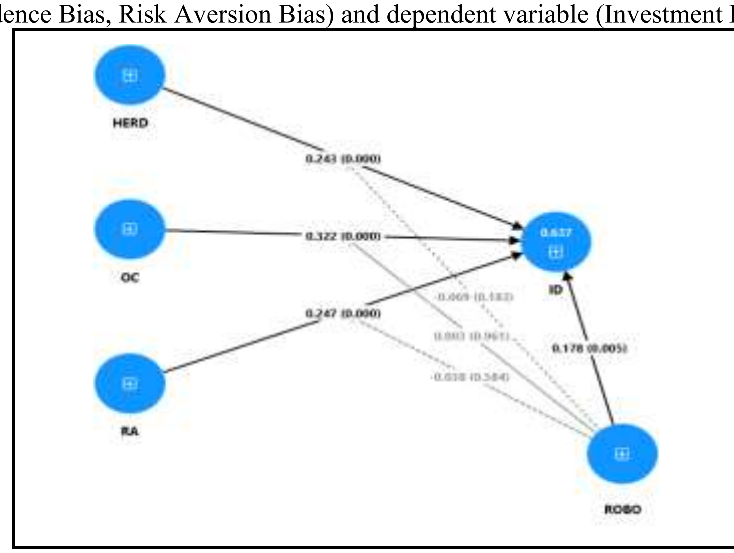

Figure 4: Moderation by Robo Advisory over Direct Relationship.

The figure above and the table below present the beta, t-statistics, p-values, and decisions for each relationship. The findings indicate that representative bias and overconfidence bias have an insignificant moderating effect on investment decisions, meaning that all hypotheses are accepted except for H7 and H9.

Table 5: Path coefficients for Moderation by Financial Literacy

Hypothesis	Beta Value	t-value	P values	Decision
H4: ROBO x OC -> ID	-0.038	0.548	0.584	Rejected
H5: ROBO x RA -> ID	-0.069	1.334	0.183	Rejected
H6: ROBO x HERD -> ID	0.003	0.049	0.961	Rejected

5. DISCUSSION

The regression analysis paints a crystal-clear picture of the cause-and-effect link between the independent and dependent variables. The findings shine a spotlight on anchoring bias, a cognitive quirk that heavily sways investment decisions. The data makes no bones about it—anchoring bias significantly skews an investor's choice of investments, with results showing a statistically significant association ($p < .000$). The hypothesis tests align seamlessly with earlier research, singing the same tune as prior findings. For instance, Owusu and Laryea (2023) revealed that investors lean on their past experiences to gauge the accuracy of their calculations and predictions. Literature echoes this sentiment, underscoring the hefty impact of anchoring bias on investment decisions. The seminal work by Tversky and Kahneman (1974) laid the groundwork, demonstrating that people cling to the first number thrown at them, whether it fits the bill or not. Ariely et al. provided a striking example: investors were asked whether the Dow Jones Industrial Average was higher or lower than an arbitrary number. Lo and behold, their judgments were warped by the first digit, underscoring how anchoring bias steers investor behavior down the wrong path. What's more, research shows that this bias doesn't discriminate—it trips up both greenhorns and veterans alike. Rabin and Schrag (1999) confirmed that both rookie and seasoned traders aren't immune, as their stock price predictions were swayed by the initial data points they encountered. Hartzmark and Sussman (2018) chipped in with another layer of insight, finding that individual investors are drawn like moths to a flame by stocks in the news, even when the headlines have zilch to do with the company's financial health. Instead of honing in on hard-nosed financial metrics, investors often chase the most glaring or readily available information—classic availability bias at play. To keep these biases at bay, investors should cast a wide net when gathering information. That means diving deep into a company's financials, spreading their bets across different asset classes and sectors, and keeping their eyes on the horizon rather than being whipsawed by market noise. By doing so, they can sidestep the pitfalls of cognitive shortcuts and make more level-headed investment decisions.

6. CONCLUSION AND IMPLICATIONS:

This paper dives into the behavioral quirks that trip up individual investors in the Indian market, shining a light on the pivotal role of robo-advisors in ironing out these biases. The primary focus is to untangle the technological hurdles industry experts face in crafting smarter, sharper robo-advisors. A secondary aim zeroes in on how investor profiling amps up the effectiveness of robo-advisory services.

The findings carry weighty implications for business leaders and financial advisors. Wealth managers have two clear paths to tread. First off, firms need to nail down a rock-solid risk profiling model to better understand their clients' needs. Robo-advisory firms should broaden the scope of their recommendations, building credibility by delivering advice that goes the extra mile (Edwards, 2018). A more ambitious, albeit painstaking, move would be to segment investors into clusters based on their risk tolerance, risk appetite, and societal demographics. Bringing behavioral economics pros on board could be a game-changer, helping firms tailor their advisory services to tackle investor biases head-on. On the awareness front, the government should roll out campaigns to educate mass-market investors on the perks of automated investment solutions.

While this study leans on quantitative methods, it does have its blind spots—chiefly, the findings aren't built for sweeping generalizations. Future research could balance the scales by taking a qualitative approach. For instance, the factors identified here could be woven into a questionnaire for a large-scale survey to gauge their impact. Additionally, probing the interplay between refined risk profiling and cutting-edge AI methods could open up exciting new avenues. Another untapped goldmine is exploring how non-tech-savvy and financially illiterate individuals from affluent backgrounds perceive robo-advisors.

Banks sit on a treasure trove of data that could supercharge investor risk profiling and algorithm design, but the real challenge lies in bridging the gap between behavioral biases and robo-advisory capabilities. Expertise in behavioral finance and psychology is the need of the hour, as current robo-advisors fall short in addressing these biases within the Indian context.

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