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Behavioural Biases and Their Impact on Investment Decision-Making: A Study of Individual Investors in India

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Abstract

Herding, Anchoring, Loss Aversion, Overconfidence, Confirmation Bias, and the Disposition Effect are the six behavioural biases whose prevalence, co-existence and Analysis to study whether biases operate in isolation or accumulate to compound decision-making impairment.

The hypothesis of mutual exclusivity was rejected as 86.8% of investors exhibit two or more biases simultaneously according to the results. In the list of predictors, Herding and Overconfidence were shown to be the strongest while Loss Aversion ranked last thus highlighting a notable divergence from the foundational Prospect Theory.

Cognitive inconsistency was discovered as 32.1% of investors simultaneously held the contradictory pairing of both Herding as well as Overconfidence. A substantial increase in decision making impairment with each additional bias was confirmed with the use of ANOVA while regression analysis established 61.3% of decision-making variation. The need for holistic, multi-bias aware approaches in investor education, financial advisory as well as regulatory policy were highlighted in the findings. compounding impact on investment decision making of 159 individual retail investors in India. A structured Likert-scale questionnaire was analysed using Random Forest Classification, One-Way ANOVA, Simple Linear Regression, and Co-occurrence

Keywords: Behavioural Finance, Investment Decision-Making, Herding, Overconfidence, Anchoring, Random Forest, Co-occurrence Analysis, Indian Retail Investors

Introduction

Financial markets have traditionally been studied by researchers with the perspective of rational decision-making, assuming that investors objectively process all available information and act in their best financial interest. The Efficient Market Hypothesis (Fama, 1970) is based on this fundamental idea, stating that asset prices at any given time reflect all available information. However, decades of real-world observation-from market bubbles to panic-driven sell-offs have made it increasingly clear that investors do not always behave rationally.

This gap between theory and reality gave rise to the field of behavioural finance, which uses psychology to learn more about how emotions, cognitive constraints, and mental shortcuts affect how people make financial decisions. Behavioural finance is based on the idea that investors tend to think irrationally in predictable ways known as behavioural biases. These biases are not mistakes but are predictable and recurring patterns that keep investors from making the best decisions.

Herding, Anchoring, Loss Aversion, Overconfidence, Confirmation Bias, and the Disposition Effect are all commonly researched biases that have been found to exist among different types of investors. However, very little research has been done on how these behaviours influence each other when they occur together within a single person, and whether having multiple behaviours at once will impair decision-making to a greater extent than having only one.

Literature Review

1. Behavioural Finance: Background

The Efficient Market Hypothesis (Fama, 1970) captures the view that investors are perfectly rational and make decisions based solely on available information which is assumed by traditional finance. However, real-world investor behaviour frequently contradicts this assumption. With the aim to bridge this gap, behavioral finance emerged. Psychology and economics were combined to explain why investors often act irrationally. Kahneman and Tversky's (1979) Prospect Theory acted as its theoretical foundation, depicting that people feel the pain of losses more strongly than the pleasure of equivalent gains, a concept that underlies many of the biases studied in this research.

2. Review of Key Behavioural Biases

Herding

When investors follow the crowd in comparison to their own analysis, it is known as herding. The social conformity experiments of Asch (1956) were traced back by Tripathy (2014) and found it to be one of the most common biases among individual investors. The fact that periods of market uncertainty cause herding to intensify was noted by Shukla et al. (2020). In the present study, Herding emerged as the strongest predictor of biased decision-making (25.77% feature importance).

Anchoring

According to Tversky & Kahneman (1974), anchoring can be defined as the fixation on a past price or reference price in comparison to a simple evaluation of the asset based on its current fundamentals. That Indian investors typically use their purchase price as an anchor when deciding whether to buy or sell was discovered by Dangi and Kohli (2018). In their Ghanaian study Nkukpornu et al. (2020) found anchoring to have a high impact on investment decisions. Anchoring was found to have the highest average prevalence score among all six biases (3.47/5) in this study.

Loss Aversion

Loss aversion describes the tendency to feel losses more painfully than equivalent gains which is a direct outcome of Prospect Theory (Kahneman & Tversky, 1979). Tripathy (2014) found a statistically significant relationship between loss aversion and investment decisions (p = 0.000). Loss Aversion ranked last in predictive importance at 6.44% in the present study, despite its prominence in literature which represents a noteworthy divergence and warrants further investigation. It can be described as the tendency to feel the pain arising from losses more significantly than the joy from equivalent gains.

Overconfidence **Overconfidence is an excessive belief in one's own knowledge and abilities. It is one of the most widely documented biases in behavioural finance. Chaubey and Raj (2024) found it was the most recognised cognitive bias among investors (60% of respondents). Most investors credit success from investment to their own knowledge of the market as found by Tripathy (2014). The present study found Overconfidence to be the second most important predictor (25.68%) and found that post-graduate investors showed the highest overconfidence scores suggesting education can paradoxically amplify this bias.**

Confirmation Bias **Ignoring contradictory evidence while simultaneously seeking information that supports existing beliefs is what is known as confirmation bias, (Dangi & Kohli, 2018). A lack of properly diversified portfolios and missed warning signals have sprung up as a result of this, a fact noted by Chaubey and Raj (2024). Confirmation Bias ranked fifth in predictive importance at 11.15% but was seen to frequently co-occur with Anchoring and Herding.**

Disposition Effect **The tendency of selling winning investments too quickly while holding the losing ones for a longer period is what is known as The Disposition Effect, identified by Shefrin and Statman (1985). This effect was documented across Indian, Chinese, and Taiwanese markets by Shukla et al. (2020). Dangi and Kohli (2018) link it to investors who avoid confronting poor decisions. In this study, Disposition ranked fourth in importance (12.14%) and co-occurred with Anchoring in 67 out of 159 respondents.**

3. Co-existence of Biases and Research Gap Prior research mainly studies biases in isolation. However, with the use of factor analysis Dangi and Kohli (2018) showed that investors exhibit clusters of multiple biases simultaneously and hence six archetypes of investors were created. When four biases were studied together, 99.7% of variation in investment decisions were explained which is in stark contrast to any single bias alone. A key research gap: developed markets are the hotspot for most studies relating to behavioral finance and are known to examine individual biases in comparison to their combined effect was identified by Shukla et al. (2020). Using a Random Forest model, ANOVA, and regression analysis, six biases were examined simultaneously among Indian investors to address this gap, hence providing empirical evidence of the coexistence, contradictory nature as well as the compounding effect of biases and their effect on decision-making.

Study Area This study focuses on understanding how behavioural biases influence the investment decisions of individual retail investors. Six key biases form the center of this report, namely Herding, Anchoring, Loss Aversion, Overconfidence, Confirmation Bias, and the Disposition Effect which are among the most frequently documented biases in behavioural finance literature.

Primary data is collected from 159 individual investors across varying demographic profiles which includes age, income, education, investment experience, and risk appetite. Due to the difference of the behavioural dynamics from retail investors, institutional investors, professional fund managers, or algorithmic trading entities are not included in the study.

The analysis is confined to self-reported perceptions and behavioural tendencies as captured through a structured Likert-scale questionnaire. A Random Forest Classification model is employed to rank the biases by their predictive importance, supported by ANOVA and regression analysis to test whether the number of biases an investor simultaneously exhibits has a measurable and compounding effect on their decision-making behaviour.

It does not incorporate actual trading data or portfolio performance metrics. Individual investors in India are represented with a broad geographical scope, hence making it most applicable in the context of Indian retail investment. The study does not seek to generalise findings to international markets without further validation.

The findings of this study contribute to the growing body of behavioural finance literature in developing markets and offer practical insights for individual investors, financial advisors, and market regulators seeking to understand and mitigate the psychological dimensions of investment decision-making.

Methodology

1. Research Design

A structured questionnaire was created with the aim to collect primary data which formed the basis for a quantitative research design. The nature of research is descriptive and correlational with the objective of explaining how prevalent behavioural biases are amongst individual investors, and further to closely examine the relationships between those biases and investment decision-making outcomes. This research aims to determine the major trends and patterns in the data and not to examine the cause.

2. Sample and Data Collection

Primary data was collected from a total of 159 individual investors who agreed to participate in this study. An online questionnaire was created using Google Forms and convenience sampling was used to select respondents that varied in terms of age, income, education level, investment experience, as well as risk appetite. Institutional investors and professional fund managers are not indeed as the sample is limited to individual retail investors.

Table 1: Demographic Profile of Respondents

Demographic	Categories	Demographic	Categories
Age Group	18–20, 21–30, 31-40, 40+	Monthly Income	Below 25000, 25000-50000, 50000-100000, 100000+
Education	UG, PG, Others	Risk Appetite	Very Low to Very High
Experience	<1 yr, 1–3 yrs, 3–5 yrs, 5+ yrs	Sample Size	159 Respondents

3. Questionnaire Design

A 5-point Likert scale that ranged from 1, indicating Strongly Disagree to 5, indicating Strongly Agree was used to measure 20 questions which were grouped into six bias categories as outlined in Table 2 and a specific behavioural bias was captured through each question. Five questions (Q13, Q14, Q15, Q17, Q19) were reverse-coded to control for acquiescence bias meaning a higher response on these questions actually indicates a lower level of the corresponding bias. Reverse coding was applied during data preparation prior to analysis.

Table 2: Question-to-Bias Mapping

Behavioural Bias	Questions	Nature
Herding	Q1, Q8, Q12	Standard
Anchoring	Q2, Q7, Q16, Q18	Standard
Loss Aversion	Q6, Q13, Q14, Q17	Q13, Q14 (Reverse Coded) Q17
Overconfidence	Q5, Q9	Standard
Confirmation Bias	Q4, Q11, Q15	Q15 (Reverse Coded)
Disposition Effect	Q3, Q10, Q19, Q20	Q19 (Reverse Coded)

4. Reliability Testing — Cronbach's Alpha

The use of Cronbach's Alpha for measuring internal consistency among the questions in each of the six bias groups indicated a lack of consistency as all the statistics generated were below the acceptable threshold of 0.60. This presents a significant limitation for this investigation. This is attributed to the multidimensional nature of behavioural biases, where different questions within the same bias may capture distinct sub-dimensions rather than simply measuring one single unidimensional construct. This finding is consistent with similar challenges reported in behavioural finance survey research. The researchers continue the analysis while noting this limitation of their research.

5. Bias Score Computation

For each respondent, a bias score was computed for each of the six behavioural biases by calculating the arithmetic mean of the responses to the corresponding questions (after reverse coding where applicable). This produced six individual bias scores per respondent, each ranging between 1 and 5. A score above the midpoint of 3 was used as the threshold to classify a respondent as exhibiting that particular bias. An overall composite bias impact score was also computed by averaging all six bias scores, which served as the dependent variable in the regression and ANOVA analyses.

6. Hypothesis

Hypothesis 1:

H0: Investors do not simultaneously exhibit multiple behavioural biases; behavioural biases are mutually exclusive in investment decision-making.

H1: Investors simultaneously exhibit multiple behavioural biases, including mutually contradictory biases, indicating cognitive inconsistency in investment decision-making.

Hypothesis 2 (H2):

H02: The number of behavioural biases simultaneously exhibited by an investor has no significant effect on their investment decision-making behaviour.

H12: Investors who simultaneously exhibit a higher number of behavioural biases demonstrate significantly more impaired or irrational investment decision-making behaviour compared to those exhibiting fewer biases.

7. Random Forest Classification Model

A Random Forest Classification model was built to study the significance of the six behavioural biases on investment decision-making. The composite bias impact score was converted into a binary target variable - High Bias Impact (score above 3) and Low Bias Impact (score at or below 3). The dataset was split in two ways, with 80% as data for training while the remaining 20% was testing data. To prevent overfitting, 100 decision trees with a maximum depth of 5 in were used to train the model. Using accuracy, precision, recall F1-score, and 5-fold cross-validation as the basis, the model performance was evaluated. Feature importance scores extracted from the model were used to rank each bias by its relative contribution to predicting investment decision-making outcomes.

8. One-Way ANOVA

A one-way Analysis of Variance (ANOVA) was conducted to test whether investors exhibiting different numbers of simultaneous behavioural biases show significantly different investment decision-making scores. Respondents were grouped based on the number of biases they exhibited (0 through 6), and the mean composite decision score was compared across these groups. Statistical significance was assessed at the 5% level ($p < 0.05$). Hypothesis $H1_7$ which proposes the notion that investors demonstrate significantly different decision-making behaviour if they carry more biases is tested in the analysis.

9. Simple Linear Regression

In order to quantify the strength as well as direction of the relationship between the number of biases that an investor simultaneously exhibits, i.e., the independent variable and the overall composite bias impact score i.e., the dependent variable, simple regression model was performed. The coefficient of determination (R^2), indicates what proportion of variation in investment decision-making can be explained by the number of biases and the regression coefficient (β), shows by how much each additional bias impacts the decision score, all of which can be provided by the regression model.

10. Co-occurrence and Contradictory Bias Analysis

A co-occurrence analysis was conducted with the aim to test the hypothesis that investors simultaneously exhibit multiple contradictory biases. Using a midpoint of 3, each respondent was classified as exhibiting or not exhibiting each of the six biases. A co-occurrence matrix was used to graphically represent the number of investors that simultaneously exhibited each possible pair of biases. Overconfidence and Loss Aversion, and Herding and Overconfidence, which are theoretically contradictory bias pairs were specifically examined to identify the proportion of investors carrying both contradictory biases at the same time, providing direct evidence of cognitive inconsistency.

Experiments and Results

1. Descriptive Statistics — Bias Prevalence

First, the average bias score for each of the six behavioural biases was computed for all 159 respondents. Each score represents the mean Likert response (1–5) for the questions mapped to that bias, ensuring the reverse-coded questions were adjusted prior to computation. Keeping the midpoint as 3, any score above indicates that the bias is prevalent among the sample.

With the exception of Loss Aversion, all biases scored above the midpoint of 3 hence signifying that a majority of the investors in the sample are known to show moderate to high levels of the aforementioned biases. Anchoring emerged as the most prevalent bias (3.47) followed by Herding (3.33), while Confirmation (3.06) and Loss Aversion (2.76) were the least prevalent (2.76). Furthermore, 116 out of 159 respondents (73%) were classified as High Bias Impact investors, meaning their overall composite bias score exceeded the midpoint which is a strong indication that behavioural biases are widespread among individual investors in the sample.

2. Reliability Analysis — Cronbach's Alpha

Cronbach's Alpha was used to assess the internal consistency of the questions within each bias group. All six bias groups returned a score that fell below the acceptable threshold of 0.6, not demonstrating a good degree inter-item reliability. A limitation of this study is highlighted in these low values which can be attributed to the multidimensional nature of behavioural biases i.e., it is possible to capture unique sub-dimensions using different questions within the same bias as compared to a single unidimensional construct. As the correlation between the individual questions was relatively low, each question measures a feature of the bias that is distinct from all others rather than measuring different aspects of the same bias. This finding is consistent with similar challenges found in other similar behavioural finance research studies and the study continues to analyse this limitation in a full and transparent manner.

3. Random Forest Classification Model

A Random Forest Classification model was built to assess the predictive importance of the six behavioural biases on investment decision-making. The model was trained on 80% of the data (127 respondents) and tested on the remaining 20% (32 respondents).

Table 3: Random Forest Model Performance

Metric	Value	Interpretation
Test Accuracy	81.25%	26 out of 32 respondents correctly predicted

Cross-Validation Accuracy	87.36%	Average across 5-fold CV — model is reliable
High Bias Precision	82%	Correct 82% of the time when predicting High Bias
High Bias Recall	90%	Identified 90% of all actual High Bias investors
Low Bias F1-Score	0.73	Slightly weaker — fewer Low Bias samples available

An accuracy of 81.25% as well as a mean cross-validation accuracy of 87.36%, was achieved with this model hence confirming strong and consistent predictive reliability. High Bias investors rather than Low Bias ones were more accurately pinpointed with this model, which is expected given the disparity, 116 High Bias respondents versus only 43 Low Bias respondents.
The feature importance scores extracted from the Random Forest model reveal the relative contribution of each bias to predicting investment decision-making outcomes. 51.45% of the model's predictive power was accounted for with Herding (25.77%) and Overconfidence (25.68%) together hence making the two of them dominant drivers of biased investment decision-making in this sample. Herding, Overconfidence, and Anchoring, the top three biases collectively explain 70.26% of decision-making behaviour. Additionally, in spite of Loss Aversion being one of the most widely discussed biases in the literature of behavioural finance, ranked last with an importance of 6.44%.

4. Co-occurrence Analysis

To determine if there are multiple behavioural biases present in an investor's decision-making (H1), a co-occurrence analysis was employed. Respondents were coded as having a bias (based on their score) if the response exceeded 3 (the midpoint of the scale). The total number of simultaneous behavioural biases were then calculated based on the sample of respondents.86.8% (150/159) of all respondents were determined to have more than one bias, and 66.6% (108/159) of respondents exhibited three or more biases at the same time. H1 is also supported by these results and H0 (probabilities of having bias are equally likely) is rejected; therefore, it is clear that behavioural biases are not mutually exclusive. No investor has a single most related behavioural bias; therefore, each investor has multiple overlapping behavioural biases that affect their investment decisions.

5. One-Way ANOVA Results

An analysis was done to look for differences between the amounts each various investor exhibited towards making a decision concerning their respective scores based on the number of behavioural biases exhibited. Significant differences ($F = 41.93$, $p = 0.000$) indicates that the amount of bias or number of behavioural biases present within a single investor may have some effect on that investor's ability or potential to behave and make proper investment decisions.

Table 4: Mean Decision Score by Number of Biases (ANOVA)

Number of Biases	Mean Score	Investors (n)	Std. Deviation
0 Biases	2.671	9	0.453
1 Bias	2.694	12	0.327
2 Biases	2.978	30	0.170
3 Biases	3.179	42	0.145
4 Biases	3.346	50	0.174
5 Biases	3.564	14	0.120
6 Biases	3.667	2	0.118

The mean decision score increases consistently with every additional bias from 2.671 for investors with no biases to 3.667 for those exhibiting all six. This perfectly monotonic relationship is a particularly strong finding, indicating that the accumulation of biases does not plateau but continues to compound with each additional bias. $H1_7$ is therefore supported and $H0_7$ is rejected.

6. Simple Linear Regression Results **A simple linear regression was run to facilitate the evaluation of the relationship between the number of biases exhibited at the same time by an investor and their overall investment decision-making score. The model showed that the number of biases was a statistically significant predictor of their investment decision-making behaviour ($R^2 = 0.613$, $p = 0.000$). A 0.19-point increase in an investor's decision-making impairment score occurs for each additional bias they exhibit at the same time. For example, an investor who exhibits 4 biases has approximately a 0.76-point higher score than an investor that exhibits no biases, a significant difference on a scale of 1–5. Collectively, these results along with ANOVA findings provide strong empirical support for $H1_7$.**

7. Contradictory Bias Co-existence Analysis **In order to evaluate the hypothesis (H1) further, a total of two biases that are theoretically opposite in nature were used to examine how many investors exhibited their combination of cognitive dissonance at the same time. In total, 19 of 159 investors (11.9%) exhibited the combination of 'overconfidence' (an overconfident investor should take more risks) and 'loss aversion' (an irrational fear of a loss). More significantly, 51 out of 159 investors (32.1%) concurrently exhibited both 'herding' and 'overconfidence' (i.e., an investor follows what everyone else is doing while simultaneously believing they (e.g., themselves) are superior to others). Thus, one-third of investors in this sample exhibited the cognitive inconsistencies described above. A possible explanation for this phenomenon is the overconfidence of these investors regarding their ability to time the crowd (i.e., they believe they can better time the crowd than other**

investors). The results clearly show support for the hypothesis (H1) and provide strong evidence of cognitive inconsistency.

8. Demographic Analysis

The bias score analysis revealed that the five tested demographic variables (age group, education, monthly income, investment experience, and risk appetite) can help provide a clearer understanding of the behaviour of investors affected by specific biases and to identify those who are in the best position to affect these biases.

When looking at specific bias scores by ages, it was discovered that middle-aged individuals (36–45) had both the highest scores of bias due to the neurobiological effects of residing in a phase of life with more financial obligations and implicitly more time invested.

In contrast, younger (18–25) individuals did not exhibit as much bias, which suggests that significant age-based influences on the amount of bias experienced by an investor may increase through achieving greater amounts of financial obligations or by being an investor for a longer period of time.

Contrarily, consistent with the expectation of higher education increasing the level of confidence among investors, post graduate investors (3.65) when compared to undergraduate investors (3.20) reflected this effect as post graduate investors have developed higher levels of self-esteem than their undergraduate counterparts.

Bias scores tended to peak for Herding and Anchoring type behaviours at about the 3 - 5-year experience mark, then tapering off slowly when surpassing the 5 - year experience mark, indicating that simply gaining additional levels of experience has little impact on the removal of these behavioural biases. Investors who possess similar amounts of experience will likely carry reasonably high confidence levels in how much they have gained from their experience base. Conversely, because of the amount of time each investor has been gaining their experience; they might also be at a higher risk for conducting any type of biased analysis as a result of their combined experience level with others.

In much the same way as indicated above, investors who have high-risk appetites generally exhibit higher than average scores in both Overconfidence and Herding with an equally lower than average score in Loss Aversion. It is a logical deduction that those investors who have a higher propensity towards risk taking would exhibit lower levels of concern when losing money, but tend to have greater levels of confidence in making decisions as well as more often relying on external sources (markets) rather than making independent and objective analyses based on their level of experience.

9. Bias Combinations and Investor Profiles

The results of the various analyses (pairwise and triplet co-occurrence classification, ANOVA, regression, and co-occurrence analysis) consistently show that behavioural biases do not function independently; they function together, interact with each other and in combination negatively impact investment decision-making in a consistent manner that has empirical significance across samples of investors. Herding and anchoring represent the largest number of co-occurring biases (i.e., 48.4% of investors) and are tied with each other as the largest number of investors with co-occurring biases within the sample. Anchoring co-occurs with the other four co-occurring biases more frequently than any other single bias pair, indicating that anchoring is probably the most common and persistent behavioural bias experienced by investors in the study. The largest three-bias cluster is herding, anchoring, and overconfidence, with 27% of investors having this behavioural cluster (or 1 in 4 investors in the sample); herding, anchoring, and disposition also represent a three-bias cluster that has been identified as having existed for 27% (or also 1 in 4) of investors in the sample.

The combining of the data produced a profile of a typical biased investor who comes from this study; they are an investor who tends to follow the herd (Herding), believes that historical prices reflect future price movements (Anchoring), and believes they are far more capable of making good investment decisions than they actually are (Overconfidence). This profile reflects the literature on behavioural finance and can assist financial advisers with their attempts to identify and help their clients' investments be less biased.

Discussion and Conclusion

This research will pursue the purpose of determining if individual investors concurrently demonstrate various behavioural biases as well as if these behavioural biases produce an accumulative compounding effect that affects investment decision-making. Through all statistical methods (Random Forest Classification, ANOVA, Regression, Co-occurrence Analysis), it was concluded that behavioural biases do not exist independently. Multiple behavioural biases can coexist, influence one another, and, collectively, detract from how investors make decisions based on the results of this study, which show a statistically significant correlation between behavioural biases and investment decision-making.

The two main factors contributing to biased investment decisions were determined through Predictive Modelling via Random Forest Analysis, as well as the predictive accuracy accounting for nearly half of the model's overall effectiveness. The factors were Herding (at 25.77%) and Overconfidence (25.68%). This is in line with Tripathy (2014) finding that Overconfidence was also identified as one of the leading individual retail investor biases; further, the findings replicate those identified by Shukla et al (2020) where Herding was identified as an extremely common bias across all types of market conditions.

Another important finding was how mutually reinforcing the two biases of both Overconfidence and Herding were. For example, an overconfident investor will have a strong desire to independently select the best stocks based upon their belief that they have selected the best option; co-occurrence analysis revealed that 32.1% of all investors exhibited both Herding and Overconfidence (during the same time-frame); therefore, this was also indicative of the fact that even when choosing independently of one another (Herding) they also viewed themselves as being superior (in terms of Overconfidence).

While loss aversion is often viewed as a key behavioural finance bias, it was ranked lowest in terms of its predictive ability (6.44%) and had the lowest average prevalence score (2.76 out of 5) in the present study of all 6 biases examined. This finding contrasts sharply with Tripathy's (2014) work, which found a statistically significant effect for loss aversion on making investment decisions, and also Kahneman and Tversky's (1979) Prospect Theory, which positioned loss aversion as fundamental to irrational behaviour in finance.

One explanation for this discrepancy could be the demographic distribution of participants: a preponderance of younger investors (ages 18-35), who are likely to have not yet experienced any tangible losses; therefore, their loss-averse tendencies may not be strongly established. Furthermore, there has been a substantial revision to the profile of Indian retail investors, with much greater involvement of younger, more risk-tolerant investors. These younger investors appear to have more tolerance of market fluctuations, which tends to reduce any inherent loss-aversion tendencies.

Co-existence of Biases and Cognitive Inconsistency

A key finding of this research is that an overwhelming majority (86.8%) of the sample shows investors who have two or more biases at once; furthermore, approximately two-thirds (66.6%) have had three or more biases coexisting at the same time; all of which are indicators that strongly support H1. This finding is also consistent with the study conducted by Dangi and Kohli (2018), who through factor analysis found that investors formed classes of archetypes based on groups of biases or combinations of multiple biases instead of singles; this result aligns well with Nkukpornu et al.'s (2020) work in which they tested numerous biases together and found that all four of those biases explained almost all (99.7%) of the variability in investment decisions made by investors and that none of those biases could do as well by themselves if tested individually.

The evidence of cognitive inconsistency (i.e., investors carry opposing theoretically defined biases at once) is very strong here. The finding that a small percentage of investors (11.9%) display both Overconfidence and Loss Aversion at the same time suggests that the psychology of the investor does not fit into straightforward or well-defined theoretical boundaries. These individuals appear to be overconfident about their ability to generate returns and at the same time are constrained from fear of loss; as a result, their ability to make rational investment decision processes probably will be very unstable and highly irrational due to their lack of capacity to achieve either an overconfident state or a state of fear for their investment capital.

The Compounding Effect — ANOVA and Regression

The analysis ($F=41.93$, $p<0.001$) indicated that investors with different levels of concurrent biases have significantly different decision-making abilities. The unique and perfectly monotonic increase in decision-making ability, from 2.671 for investors without any biases to 3.667 for investors with all six biases, suggests not just that an investor's decision-making ability becomes impaired with each additional bias present (e.g., 1 bias= 2.671; 6 biases = 3.667), but that the impairment of an investor's decision-making ability increases exponentially with every additional bias.

This compounded nature of how multiple biases impair an investor's decision-making process is one of the foundational theoretical contributions of this study. Investors need a more comprehensive approach to understanding and combating the effects of multiple concurrent biases; therefore, financial advisors and education programs must shift their focus from studying and addressing each individual bias in isolation to recognizing and addressing the cumulative psychological toll that having multiple concurrent biases has on an investor's ability to make sound investment decisions.

Demographic Insights

The analysis of the demographics yielded several interesting results. The most surprising observation was that the post-graduate educated investors had the highest Overconfidence Score (3.65), which seemed to indicate that higher education actually increases Overconfidence, rather than decreases it. This also supports the Dunning-Kruger Effect which is well documented in regard to how increased knowledge can lead to increased overconfidence. Therefore, not only will we need to create financial literacy programs that teach about financial topics; but also create an understanding of their limitations and develop humble people, who know they have cognitive limitations.

Research has shown that the more knowledge one obtains on a subject, the more confident one becomes. Therefore, it is clear that our survey results back this statement, and indicates a need for us to create programs that teach financial literacy, and also teach people their limitations and demonstrate to them that they cannot use their financial literacy as a source of guidance because of their lack of expertise in the area of their personal financial situations, as well as teach them humility concerning their limitations concerning their own cognition.

Conclusion

Hypothesis Outcomes

H1 — SUPPORTED | H0 — REJECTED: Investors simultaneously exhibit multiple behavioural biases, including mutually contradictory ones, indicating cognitive inconsistency in investment decision-making. 86.8% of respondents exhibited two or more biases simultaneously, and contradictory bias pairs such as Overconfidence and Loss Aversion co-existed in 11.9% of investors.

$H1_7$ — SUPPORTED | $H0_7$ — REJECTED: Investors exhibiting a higher number of simultaneous behavioural biases demonstrate significantly more impaired investment decision-making behaviour. ANOVA ($F = 41.93$, $p = 0.000$) and Regression ($R^2 = 0.613$, p =

0.000) both confirmed this relationship with high statistical significance.

Practical Implications **Individual investors can benefit from using self-awareness to better understand their psychological inclinations. Knowledge of which biases one may have and how they may combine to compound each other is essential to making rational and disciplined investment decisions. Financial advisors and wealth managers can adopt a behavioural profile approach when giving advice to clients, and try to identify the specific combination of biases their clients have, rather than just assessing the risk and financial objectives of the clients. Regulators and investor education organisations, such as SEBI, could also build investor awareness programs to help investors see how biases combine rather than treating them independently. In addition to providing a means by which bias is available in interaction with others, such as through education, awareness programmes also need to offer skills to help the investor apply critical self-reflection.**

Limitations of the Study **While this research has some limitations, they need to be recognized. To begin with, the Cronbach's Alpha scores for each of the six bias measures fell below the acceptable level (0.60), showing that these six biases were poorly correlated with the individual question scores. This may be due to the multidimensionality of behavioural bias, where each of the individual questions is measuring a different sub-dimensional element of that bias. Secondly, the sample of 159 respondents came from a convenience sample, so there is limited ability to generalize the results of this study to the larger population of Indian investors Third, all data used in this study are based upon self-reported data from a Likert-type survey, which is susceptible to social desirability bias and inconsistency in responses. Finally, the study does not have any actual trading data or portfolio performance measures to measure the quality of decision-making more objectively.**

Scope for Future Research **The limitations of this study could be addressed in future research by sampling larger and more representative samples of research participants using probability sampling techniques. The results obtained from using both actual trading data and self-reported questionnaire data may provide more objective data regarding the relationship between exhibiting bias and investment performance. Future research could also incorporate the use of Structural Equation Modelling (SEM) in order to model the set of interrelated relationships among different biases and how those biases affect decision-making, ultimately leading to a better understanding of how different biases may interact with one another. Longitudinal studies following the**

same set of investors over time may also help to identify how susceptibility to biases evolve over time based on investors' experience and changes in market conditions.

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Appendix

Data Source : **https://docs.google.com/forms/d/e/1FAIpQLSfHoRPjLc6fmI-oaH5x2XJzfdQ_5mOoJux9D1W2jIfCw6QpdQ/viewform**

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