

Major Research Project

Impact of Behavioral Biases and Investment Decision Making

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DECLARATION

I, Partha Sarthi Sharma, MBA (2024–2026) Student, Delhi School of Management, Delhi Technological University, do hereby certify that the Major Research Project titled: “Impact of Behavioral Biases and Investment Decision-Making” is an original work submitted by me as partial fulfilment of the Master of Business Administration degree requirements. This project work has been accomplished by me, and the research findings included herein are based upon my own effort and analysis. To the best of my belief and knowledge, this work is not submitted for any other university or institution to any degree, diploma, or certificate.

**Signature (Student
name) Roll No:**

Date:

Place:

CERTIFICATE

Mr. Partha Sarthi Sharma , Roll No. 24/DMBA/162 has submitted the Major research project “Impact of Behavioral Biases and Investment Decision-Making” in partial fulfilment of the requirements for the award of the degree of Master of Business Administration (MBA) from the Delhi School of Management, Delhi Technological University, New Delhi during the academic year 2025- 26.

(Dr. Mohit Beniwal) (Dr.Saurabh Agrawal) Head (DSM)

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I am thankful to the Delhi School of Management, DTU for giving me such an excellent opportunity. I would also like to thank my faculty members and friends from Delhi School of Management, DTU, who supported me in the project work as well as extended their help and support, interest, and valuable hints in doing my study.

EXECUTIVE SUMMARY

The study focuses on five major behavioral biases: overconfidence (thinking you know more than you do), loss aversion (hating losses more than loving gains, which leads to selling winners too soon and holding losers too long), anchoring (fixating on initial information like a stock's purchase price), herd mentality (following the crowd), and confirmation bias (only paying attention to news that backs your beliefs). These biases, grounded in ideas like Kahneman and Tversky's Prospect Theory, explain why investors might act impulsively, overtrade, or get swept up in market frenzies, causing bubbles or crashes that traditional theories struggle to predict.

To understand these effects, the study surveyed 70 retail investors in Delhi NCR using an online questionnaire. The group was varied: half men, half women (41.43% each), mostly aged 25–34 (30.36%), and often earning less than ₹3,00,000 a year (38.57%). Many had 1–3 years of investing experience (30%). Using tools like Excel and SPSS, the study analyzed data with stats like frequency counts, Chi-square tests, ANOVA, and regression to see if things like gender, age, or experience shaped risk-taking, crowd-following, or confidence in familiar investments.

The results did not show statistically significant relationships between gender and risk preferences ($p = 0.409$), experience and following the crowd ($p = 0.400$), or age/experience and confidence in known investments ($p = 0.577$ and 0.509). Even how skilled people thought they were did not significantly predict their confidence ($p = 0.966$). However, certain patterns were observed: 43% preferred a balanced approach to risk, 37% were very likely to follow market trends, and 40% leaned heavily on media for guidance, hinting that biases play a big role.

The findings suggest that behavioral biases can influence investors, their impact might depend on specific situations, like market conditions or cultural factors, which need more study. To support better investment decision-making, the study suggests running workshops to teach about biases, offering tailored advice from financial planners, creating apps that nudge people away from impulsive moves, and having regulators like SEBI add warnings about crowd-driven risks. These steps could empower Delhi NCR investors to build stronger financial futures and help keep India's markets steady.

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CHAPTER 1

INTRODUCTION

Financial markets are dynamic systems where prices and investment outcomes are shaped by the decisions of many participants. Market movements, asset prices, and investment performance are largely influenced by the collective decisions of investors. Therefore, understanding investor decision-making is essential for explaining market behaviour, asset pricing, and portfolio performance. Traditional finance has long assumed that investors behave rationally and that markets efficiently reflect available information. However, market anomalies, irrational investment behaviour, and financial crises have challenged these assumptions. These real-world events made people question those traditional ideas. These limitations contributed to the development of behavioral finance. Behavioral finance combines psychology and finance to explain how investors actually behave while making financial decisions.

1.1. Background and Conceptual Foundations:

Traditional Finance (TF)

Financial markets are continuously changing environments where the decisions of different participants influence outcomes. To understand price movements and investment choices, it is important to examine how investors think and behave in the market.

Traditional finance explains investment behaviour through the assumption of rational investors and efficient markets. But in reality, we see strange things happening, people doing unexpected factors, and big financial issues popping up. For this reason, behavioral finance has gained importance as an alternative approach. It integrates psychological insights with financial theory to provide a more realistic understanding of investor behaviour.

Behavioral Finance (BF)

Behavioral finance says forget the idea that investors are always completely rational. Real people don't work like that—they're complex, get caught up in their own psychological state, and let emotions or what everyone else is doing mess with their decisions. Instead

of some perfect "rational human," it's about actual investors who distort, take shortcuts in their thinking, or panic when the market declines. People like Daniel Kahneman, Amos Tversky, and Richard Thaler started this whole thing, mixing psychology with finance to explain why investors act in weird but predictable ways. So when the market becomes volatile, it's not just about bad info—it's because investors are influenced by emotions, perceptions, and cognitive limitations rather than acting like perfectly rational calculators.

Investment Decision-Making Process

- The investment decision-making process involves:
 - Defining investment goals and time horizons.
 - Assessing financial position and risk tolerance.
 - Allocating assets and diversifying portfolios.
 - Selecting investment instruments and strategies.
 - Monitoring and rebalancing portfolios as required.

Traditional finance assumes that investors make financial decisions rationally, whereas behavioral finance argues that does not fully agree with this view because our biases mess up every step, often leading to pretty bad financial decisions.

1.2. Behavioral Biases in Investment Decisions:

Behavioral Finance identifies several psychological concepts that explain irrational financial behavior. These include:

- Bounded Rationality – Limited capacity to process information and make optimal decisions.
- Heuristics – Mental shortcuts that simplify decision-making but can lead to consistent errors.
- Emotional Influences – Feelings such as fear, greed, and regret significantly impact choices.
- Framing Effects – Different presentations of identical information can influence decisions.
- Mental Accounting – The tendency to treat money differently depending on its source or intended use.

This study focuses on five key behavioral biases:

- Overconfidence Bias – Overestimating one’s knowledge or forecasting ability, leading to excessive trading and risk-taking.
- Loss Aversion – The pain of losses is felt more deeply than the pleasure of gains. This bias underpins the Disposition Effect—the tendency to sell winners early and hold onto losers too long.
- Anchoring Bias – Relying too heavily on initial information (e.g., purchase price) when making subsequent judgments.
- Herd Mentality – Following crowd behavior rather than conducting independent analysis, often contributing to bubbles and crashes.
- Confirmation Bias – Seeking out information that supports existing beliefs while ignoring contradictory evidence.

These biases often interact, compounding their individual effects and making investor behavior even more complex and less rational than classical models predict.

1.3. Objectives of the Study:

The primary objectives of this research report are:

1. To define the core concepts of behavioral finance and elucidate its fundamental assumptions, contrasting them explicitly with those of traditional finance theory.
2. To identify, define, and describe the characteristics of five key behavioral biases prevalent in investment decision-making: Overconfidence, Loss Aversion (including the Disposition Effect), Anchoring, Herd Mentality, and Confirmation Bias.
3. To provide a concise overview of the historical development of behavioral finance as a field, recognizing major theoretical contributions (such as Prospect Theory) and the influence of key figures (including Kahneman, Tversky, and Thaler).
4. To analyze the documented consequences of these behavioral biases on investment outcomes, including effects on returns, risk exposure, and overall portfolio performance.

5. To examine the role of behavioral biases in explaining market-level phenomena and anomalies, such as market overreaction, excess volatility, asset bubbles, and crashes.
6. To review and critically evaluate the primary research methodologies (including surveys, experiments, trading data analysis, case studies, and neurofinance) employed within behavioral finance to investigate investor biases and their effects.

1.4 Scope of the Study:

This research project will focus on the following aspects:

- Target Population: The primary focus will be on retail investors in Delhi NCR who directly participate in the capital markets (e.g., investing in stocks, mutual funds, bonds). The study may consider different segments of retail investors based on demographic and socio-economic factors.
- Geographical Scope: The study will be conducted in Delhi NCR; the initial phase of the study may focus on investors within this region and potentially expand later.
- Types of Investment Decisions: The study will examine various aspects of investment decision-making, including:
 - Asset allocation across different asset classes.
 - Selection of specific securities or investment products.
 - Timing of market entry and exit.
 - Frequency of trading.
 - Level of diversification in portfolios.
 - Reaction to market news and events.
 - Adherence to long-term investment plans.
- Behavioral Biases Under Investigation: The study will focus on a selected set of prominent Behavioral biases relevant to investment decision-making, which may include: overconfidence, anchoring bias, loss aversion, herding bias, availability bias, confirmation bias, and framing effects.
- Data Collection Methods: The research will likely employ a combination of quantitative and qualitative data collection methods, such as:
 - **Surveys:** To gather data on investors' demographic profiles, investment behaviours, awareness of biases, and susceptibility to specific biases.

- **Questionnaires:** To assess the presence and strength of various Behavioral biases among investors.

This project examines how behavioral biases influence investment decisions in Delhi NCR. The findings may help in developing better investor education and guidance strategies that encourage more rational decision-making, setting them up for long-term financial outcomes and keeping India's capital markets steadier.

CHAPTER 2

Literature Review

This literature review examines the existing body of knowledge related to the impact of behavioral biases on investment decision-making. It explores foundational theories, key findings from empirical studies across various contexts, and the evolution of research in this interdisciplinary field. The review highlights the significance of behavioral finance as a departure from traditional finance, examines the prevalent biases affecting investors, and discusses their consequences on investment outcomes.

2.1 Prospect Theory

Lin, H.-W. (2019) Prospect Theory is developed by Kahneman and Tversky, Prospect Theory is widely regarded as the most accurate descriptive model of how individuals make decisions when faced with probabilistic outcomes, particularly in experimental settings. It challenges the core tenets of Expected Utility Theory by demonstrating systematic psychological patterns in risk evaluation. The theory comprises several key elements:

1. Reference Dependence: Individuals evaluate outcomes not in terms of absolute final wealth, but as gains or losses relative to a specific reference point. This reference point is often the status quo, but in investment contexts, it is frequently the initial purchase price of an asset. The framing of an outcome as a gain or a loss dramatically affects its perceived value.

2. Loss Aversion: This is perhaps the most recognized feature of Prospect Theory. It posits that the negative psychological impact (disutility) of a loss is significantly greater than the positive impact (utility) of an equivalent gain. The value function in Prospect Theory is steeper in the domain of losses than in the domain of gains, often quantified by a loss aversion coefficient (λ) typically estimated to be around 2 or 2.25, meaning a loss feels roughly twice as bad as an equivalent gain feels good.

3. Diminishing Sensitivity (S-shaped Value Function): The subjective value attached to gains or losses exhibits diminishing sensitivity as the magnitude increases away from the reference point. This means the difference between a \$100 gain and a \$200 gain feels larger than the difference between a \$1000 gain and a \$1100 gain. This results in a value function

that is concave for gains (implying risk aversion in the domain of gains – preferring a sure gain over a gamble with equal or higher expected value) and convex for losses (implying risk-seeking in the domain of losses – preferring a gamble over a sure loss of equal or lower expected value). This pattern of risk aversion for gains and risk-seeking for losses is known as the "reflection effect".

4. Probability Weighting: Individuals do not perceive probabilities linearly. They tend to overweight small probabilities (making unlikely events seem more probable than they are) and underweight moderate to high probabilities (making likely events seem less certain). This is represented by a non-linear probability weighting function, $\pi(p)$, which transforms objective probabilities into subjective decision weights.

Prospect Theory involves two phases: an editing phase, where professionalspects are simplified, coded as gains or losses relative to the reference point, and potentially simplified using heuristics; and an evaluation phase, where the edited professionalspects are valued using the value function and probability weighting function. In finance, Prospect Theory provides a powerful framework for understanding why investors might deviate from rational utility maximization. It is most frequently invoked to explain the Disposition Effect, as the risk-seeking behavior in the loss domain encourages holding losers, while risk aversion in the gain domain encourages selling winners. It also helps explain framing effects and inconsistent risk attitudes observed in investment behavior. However, some research suggests that while intuitive, the link between standard Prospect Theory parameterizations and the disposition effect might be more complex or context-dependent than initially assumed.

2.2 Overconfidence Bias

William & Mary Online (2025) Overconfidence bias reflects an individual's unwarranted trust in their own knowledge, abilities, and the accuracy of the information they possess. It is considered a cognitive error involving aspects such as miscalibration, illusion of control, and the better-than-average effect, where individuals assume they are superior to others. This psychological distortion often leads to excessive trading activities, poor portfolio diversification, and an underestimation of potential risks, causing investors to take higher risks than they ideally should.

2.3 Loss Aversion / Disposition Effect

IIBS Bangalore (2025) Loss aversion describes the emotional tendency where individuals experience the pain of financial losses more deeply than the satisfaction derived from equivalent gains. Rooted in Prospect Theory, this bias often leads investors to behave irrationally, driven by fear of regret and influenced by mental accounting. As a result, investors may prematurely sell winning stocks to secure small profits while holding onto losing investments in the hope of eventual recovery, often avoiding risks that could actually be beneficial for portfolio performance.

2.4 Anchoring Bias

Sharma, R (2025) Anchoring bias occurs when individuals heavily depend on the first piece of information they encounter — known as the "anchor" — while making judgments or decisions. People lean on mental shortcuts and do not adjust sufficiently from their starting point, which distorts how they see things. In investing, this shows up when investors become overly dependent on what they paid for a stock or its past highs and lows, and it messes with their decisions. They'll hesitate buying a stock if it's pricier than their mental benchmark or refuse to sell if it's below some old reference point. Even the professionals, like analysts, can get thrown off by this anchoring factors.

2.5 Herd Mentality

Asif, M., Arif, K., &Guerci, E. (2021) Herding bias is when people imitate the actions of other investors instead of thinking for themselves. They are influenced by social pressure, factors like fearing they'll miss out (FOMO), or just assuming the crowd knows better. So, investors end up chasing hot stocks without doing their homework, dumping shares in a panic when the market tanks, or piling into speculative trends that contribute to bubbles or crashes.

2.6 Confirmation Bias

IIBS Bangalore (2025) Confirmation bias is when people zero in on factors that supports what they already believe and ignore anything that doesn't fit. It's like they're selectively using information to feel good about their ideas. In investing, this

means they look for good news about stocks they own, ignore warning signs, and stick with portfolios that aren't

spread out enough. This tendency reinforces overconfidence, distorts decision-making, and increases financial risk, as investors fail to objectively evaluate market conditions or alternative perspectives.

Table 1. Literature Review

Bias Name	Brief Definition	Psychological Root	Common Investment Manifestation
Overconfidence	Unwarranted faith in one's own knowledge, abilities, and the precision of one's information.	Cognitive error (miscalibration, illusion of control, better-than-average effect)	Excessive trading, under-diversification, underestimation of risk, taking too much risk.
Loss Aversion / Disposition Effect	Feeling losses more intensely than equivalent gains / Tendency to sell winners too soon and hold losers too long.	Emotional response (pain of loss), Prospect Theory value function, potentially regret aversion, mental accounting.	Holding losing stocks hoping for recovery, quickly selling stocks with small gains, avoiding necessary risks.
Anchoring	Over-reliance on the first piece of information encountered (the "anchor") when making judgments.	Cognitive heuristic (adjustment from an initial point)	Fixating on purchase price or past highs/lows for valuation, reluctance to buy above/sell below anchor points, biased analyst forecasts.

Herd Mentality	Mimicking the actions of a larger group rather than relying on independent analysis.	Social influence, emotional response (FOMO, fear), heuristic (belief in crowd wisdom).	Buying popular/hyped stocks without research, panic selling during downturns, chasing trends, contributing to bubbles/crashes.
Confirmation Bias	Seeking, interpreting, and	Cognitive bias (motivated	Selective information search (e.g., only reading positive

	recalling information that confirms pre-existing beliefs, while ignoring contradictory evidence.	reasoning, selective perception/recall)	news about owned stocks), ignoring warning signs, poor diversification, reinforcing overconfidence.
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CHAPTER 3 RESEARCH

METHODOLOGY

3.1 Research Design

This research adopts a descriptive and analytical approach. It aims to identify how different behavioral biases affect investment decisions. Descriptive research helps summarize general trends among investors, while analytical methods help uncover specific relationships between variables.

3.2 Population and Sampling Design

The target population includes individual investors from various demographic backgrounds. A non-probability convenience sampling method was adopted due to easy accessibility of participants. The final sample size consists of 70 respondents who have experience with investment activities.

3.3 Data Collection Method

Primary data was collected using a structured questionnaire via Google Forms. The questionnaire consisted of:

- Section A: Demographic Details
- Section B: Behavioral Bias Statements
- Section C: Investment Behavior Patterns

Respondents rated their agreement with bias-related statements, which helped quantify psychological tendencies.

3.4 Data Preparation and Cleaning

Responses were exported to Microsoft Excel for cleaning and structuring. Incomplete responses were excluded. Likert scale values were numerically coded, and demographic groups were categorized to ensure compatibility with statistical tools.

3.5 Analytical Tools and Techniques

The analysis was done using Microsoft Excel, SPSS. Tools included:

- Descriptive Statistics: Frequency, Percentage, Mean
- Chi-Square Test: To assess relationships between demographic factors and biases
- Linear Regression: It helps determine how strongly "Investing Experience" (e.g., years of experience) and "Perceived Investment Skills" (e.g., Worse, Same, Better) influence confidence
- ANOVA / Z-Test: To compare group-wise mean scores

Visualizations (bar/pie charts) were also created to better illustrate patterns.

3.6 Hypothesis

- HA1: There is a statistically significant association between an investor's Gender and their Risk Attitude (e.g., Risk Averse, Moderate, Risk Seeking).
HO1 (Null): There is no statistically significant association between Gender and Risk Attitude.
- HA2: There is a statistically significant association between the level of Investing Experience and the tendency towards Herd Behavior (e.g., Very Likely, Sometimes, Not at all).
HO2 (Null): There is no statistically significant association between Investing Experience and Herd Behavior Tendency.
- HA3: The mean score for Confidence in Familiar Assets (1-5) differs significantly across different Age Groups.
HO3 (Null): The mean score for Confidence in Familiar Assets (1-5) is the same across all Age Groups.
- HA4: The mean score for Confidence in Familiar Assets (1-5) differs significantly across different levels of Investing Experience.
HO4 (Null): The mean score for Confidence in Familiar Assets (1-5) is the same across all levels of Investing Experience.
- HA5: Investing Experience and Perceived Investment Skills Compared to Others significantly predict an investor's Confidence in Familiar Assets (1-5).
HO5 (Null): Investing Experience and Perceived Investment Skills Compared to Others do not significantly predict Confidence in Familiar Assets (1-5).

CHAPTER 4 DATA

ANALYSIS

This chapter examines the survey and get to know the people who shared their responses. We're talking 70 investors, with different backgrounds and investment perspectives—how they deal with risk, if they just go along with the crowd, or if they're all about what their friends or the news are saying. We checked out factors like their gender, how old they are, what school they finished, how much money they're pulling in, and how long they've been participating in investment activities. And yeah, we found some important patterns in there. Figuring this out is key to seeing why people make the financial decisions they do or how they pick up info. Like, someone's age or income level can totally change how bold they are with risks, how much they follow the pack, or if they're relying on media updates or discussions with peers. Shining a light on these differences makes the whole thing way easier to get and lets us throw out some real, practical recommendations that actually works for different types of people.

4.1. Demographic Analysis

Table 2. Demographic Table

Demographic Variable	Categories	Frequency	Percentage (%)
Gender	Male	29	41.43%
	Female	29	41.43%
	Other	4	5.71%
	Prefer not to say	8	11.43%
Age group	18-24	10	17.86%
	25-34	17	30.36%
	35-44	16	28.57%
	45-54	13	23.21%
	55 & Above	14	16.67%
Education Level	Bachelor's	16	19.05%
	Diploma	15	17.86%
	High School	17	20.24%

	Master's or Higher	22	26.19%
Annual Income	₹3,00,001 – ₹6,00,000	13	18.57%
	₹6,00,001 – ₹10,00,000	16	22.86%
	< ₹3,00,000	27	38.57%
	> ₹10,00,000	14	20.00%
Investing Experience	<1 year	18	25.71%
	>7 years	16	22.86%
	1–3 years	21	30.00%
	4–7 years	15	21.43%

Source: Own analysis using primary data

The table provides a breakdown of the surveyed group by demographic variables:

Gender: The distribution is relatively even between Male (41.43%) and Female (41.43%), with smaller percentages for Other (5.71%) and Prefer not to say (11.43%).

Age group: The largest age group is 25-34 (30.36%), followed closely by 35-44 (28.57%) and 45-54 (23.21%). The 18-24 and 55 & Above groups are smaller at 17.86% and 16.67% respectively.

Education Level: Master's or Higher education level is the most frequent (26.19%), followed by High School (20.24%), Bachelor's (19.05%), and Diploma (17.86%).

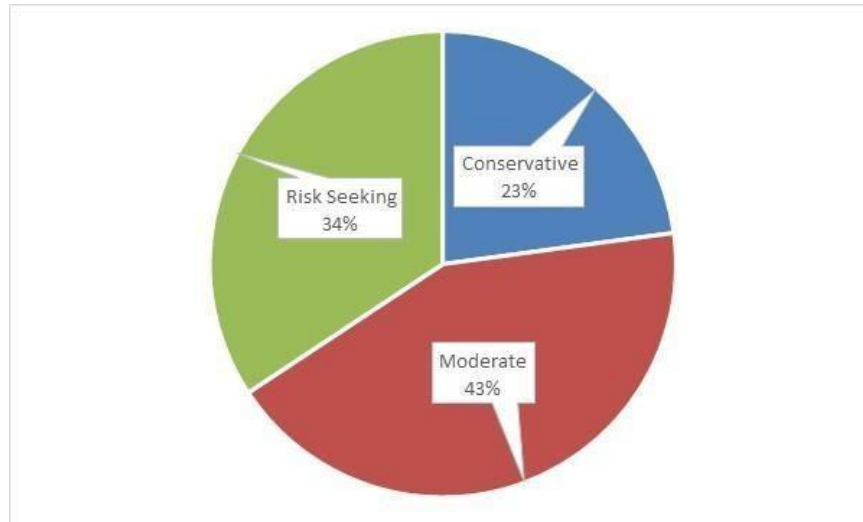
Annual Income: The largest income bracket is "< ₹3,00,000" (38.57%), followed by "₹6,00,001 – ₹10,00,000" (22.86%), "> ₹10,00,000" (20.00%), and "₹3,00,001 – ₹6,00,000" (18.57%).

Investing Experience: The most common investing experience is 1–3 years (30.00%), followed by <1 year (25.71%), >7 years (22.86%), and 4–7 years (21.43%).

4.2. Inferential Statistical Analysis

Inferential statistics describe the many ways in which statistics derived from observations on samples from study populations can be used to deduce whether or not those populations are truly different.

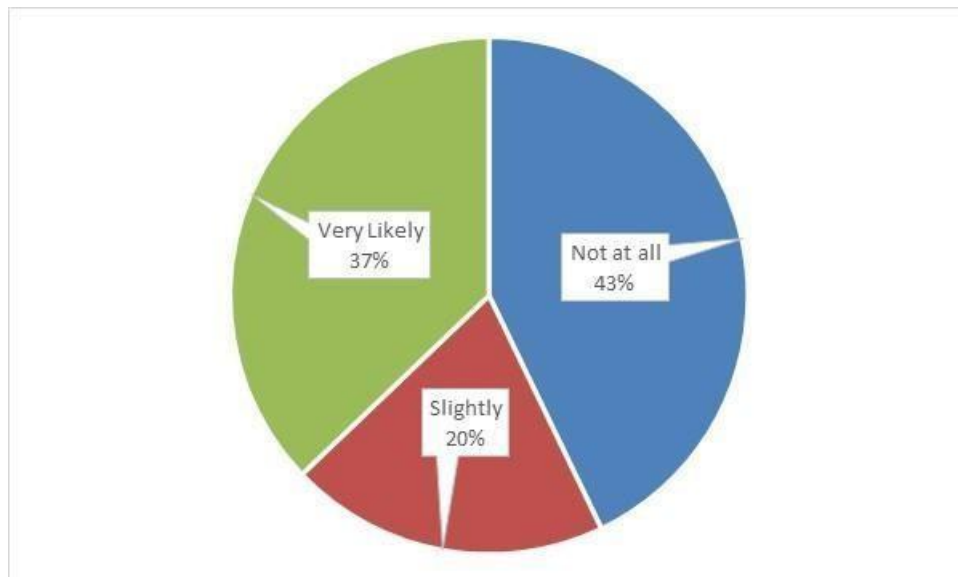
Graph 1. Risk Attitude of investors



Source: Own analysis using primary data

- Moderate risk attitude is the most common among the surveyed group, with 30 out of 70 individuals falling into this category.
- Conservative individuals represent 16 out of 70.
- Those with a Risk Seeking attitude are 24 out of 70.

Graph 2. Herd Behavior



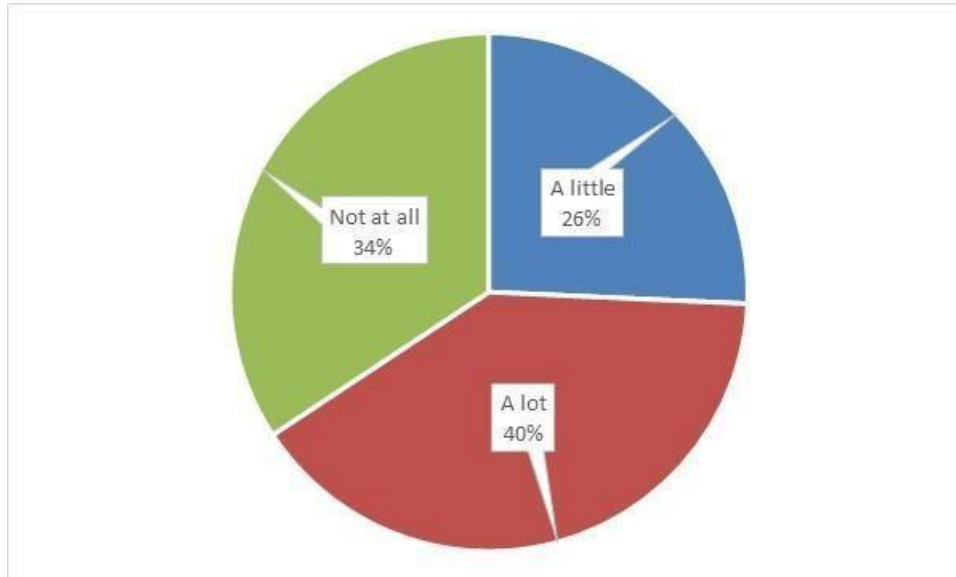
Source: Own analysis using primary data

- A significant portion of individuals (30 out of 70) indicate they are Not at all

likely to exhibit herd behavior.

- 14 out of 70 individuals are Slightly likely to exhibit herd behavior.
- 26 out of 70 individuals are Very Likely to exhibit herd behavior.

Graph 3. Reliance on Media



Source: Own analysis using primary data

- 28 out of 70 individuals rely on media A lot.
- 18 out of 70 individuals rely on media A little.
- 24 out of 70 individuals do not rely on media at all.

4.3. Hypothesis testing

Hypothesis 1 –

Null Hypothesis (HO1): There is no statistically significant association between Gender and Risk Attitude.

Alternative Hypothesis (HA1): There is a statistically significant association between an investor's Gender and their Risk Attitude.

p-value > 0.05-->reject HO1

p-value < 0.05-->do not reject HO1

Table 3: Chi-Squared test of association between Gender and Risk Attitude.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6.133 ^a	6	.409
Likelihood Ratio	8.999	6	.174
N of Valid Cases	70		

Source: Own analysis using primary data

- A Chi-square test of independence was conducted to examine the association between Gender and Risk Attitude (Conservative, Moderate, Risk Seeking).
- The case processing summary indicated that there were no missing values, and all 70 responses were included in the analysis.
- The results showed that the Pearson Chi-Square value was 6.133 with 6 degrees of freedom, and the associated p-value was 0.409. Since the p-value is greater than 0.05, the result is not statistically significant. This indicates that there is no significant association between an investor's Gender and their Risk Attitude.
- Since the p-value is greater than 0.05, the null hypothesis (H0) is not rejected. Therefore, there is no statistically significant relationship between Gender and Risk Attitude among the investors surveyed.

Hypothesis 2 –

Null Hypothesis (H02): There is no statistically significant association between Investing Experience and Herd Behavior Tendency.

Alternative Hypothesis (HA2): There is a statistically significant association between the level of Investing Experience and the tendency towards Herd Behavior.

p-value > 0.05-->reject H0

p-value < 0.05-->do not reject H0

Table 4: Chi-Squared test of association between Investing Experience and Herd Behavior Tendency.

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6.210 ^a	6	.400
Likelihood Ratio	6.188	6	.402
N of Valid Cases	70		

Source: Own analysis using primary data

- A Chi-square test of independence was conducted to examine the association between the level of Investing Experience and the tendency towards Herd Behavior (categorized as Not at all, Slightly, and Very Likely).
- The case processing summary showed that all 70 responses were valid, with no missing data.
- The Pearson Chi-Square test result was 6.210 with 6 degrees of freedom, and the associated p-value was 0.400. Since the p-value is greater than 0.05, it indicates that there is no statistically significant association between Investing Experience and Herd Behavior Tendency.
- Since the p-value is greater than 0.05, the null hypothesis (H0) is not rejected. Thus, there is no statistically significant relationship between an investor's level of Investing Experience and their tendency to exhibit Herd Behavior.

Hypothesis 3 –

Null Hypothesis (HO3): The mean score for Confidence in Familiar Assets is the same across all Age Groups.

Alternative Hypothesis (HA3): The mean score for Confidence in Familiar Assets differs significantly across different Age Groups.

Table 5: The mean score for Confidence in Familiar Assets differs significantly across different Age Groups.

Descriptives

Confidence in Familiar Assets (1-5)

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimu m	Maximu m
					Lower Bound	Upper Bound		
18-24	10	2.70	1.636	.517	1.53	3.87	1	5
25-34	17	3.35	1.539	.373	2.56	4.14	1	5
35-44	16	2.75	1.238	.310	2.09	3.41	1	5
45-54	13	3.15	1.345	.373	2.34	3.97	1	5
55 & Above	14	2.71	.994	.266	2.14	3.29	1	4
Total	70	2.96	1.345	.161	2.64	3.28	1	5

Tests of Homogeneity of Variances

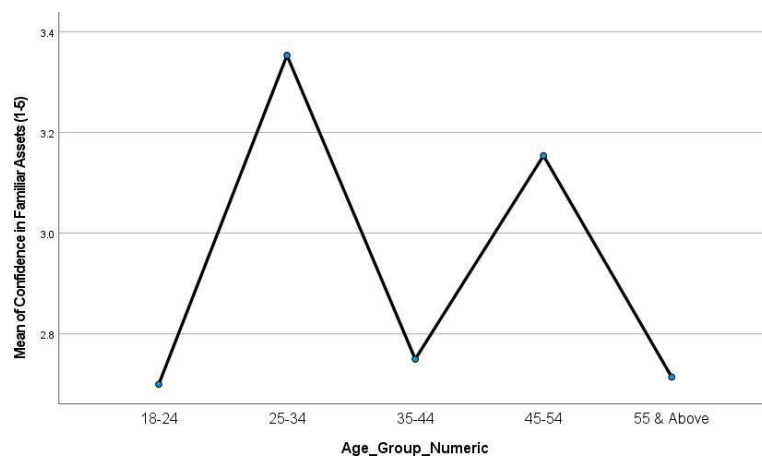
		Levene Statistic	df1	df2	Sig.
Confidence in Familiar Assets (1-5)	Based on Mean	1.887	4	65	.123
	Based on Median	1.157	4	65	.338
	Based on Median and with adjusted df	1.157	4	56.566	.339

Based on trimmed mean	1.888	4	65	.123
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ANOVA

Confidence in Familiar Assets (1-5)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.340	4	1.335	.726	.577
Within Groups	119.532	65	1.839		
Total	124.871	69			



Source: Own analysis using primary data

- A one-way ANOVA was performed to investigate whether the mean score for Confidence in Familiar Assets (1–5) differs significantly across different Age Groups (18–24, 25–34, 35–44, 45–54, and 55 & Above).
- The test of homogeneity of variances (Levene’s Test) was non-significant ($p = 0.123$), confirming that the assumption of equal variances across age groups was satisfied.
- The results of the ANOVA indicated that there was no significant difference in mean Confidence in Familiar Assets scores across the different Age Groups, $F(4, 65) = 0.726$, $p = 0.577$. This suggests that age does not significantly influence an investor’s

confidence in familiar assets.

- The mean Confidence scores for each group were:

- 18–24 years: 2.70
 - 25–34 years: 3.35
 - 35–44 years: 2.75
 - 45–54 years: 3.15
 - 55 & Above: 2.71
- While there were slight variations in mean scores among the age group, these differences were not statistically meaningful.
 - Since the p-value was greater than 0.05, the null hypothesis (H0) is not accepted. Thus, there is no significant difference in Confidence in Familiar Assets across different Age Groups.

Hypothesis 4 –

Null Hypothesis (HO4): The mean score for Confidence in Familiar Assets is the same across all levels of Investing Experience.

Alternative Hypothesis (HA4): The mean score for Confidence in Familiar Assets differs significantly across different levels of Investing Experience.

Table 6: The mean score for Confidence in Familiar Assets differs significantly across different levels of Investing Experience.

Descriptives

Confidence in Familiar Assets (1-5)

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
<1 year	18	2.72	1.447	.341	2.00	3.44	1	5
1-3 years	21	3.24	1.261	.275	2.66	3.81	1	5
4-7 years	15	3.13	1.246	.322	2.44	3.82	1	5

>7 years	16	2.69	1.448	.362	1.92	3.46	1	5
Total	70	2.96	1.345	.161	2.64	3.28	1	5

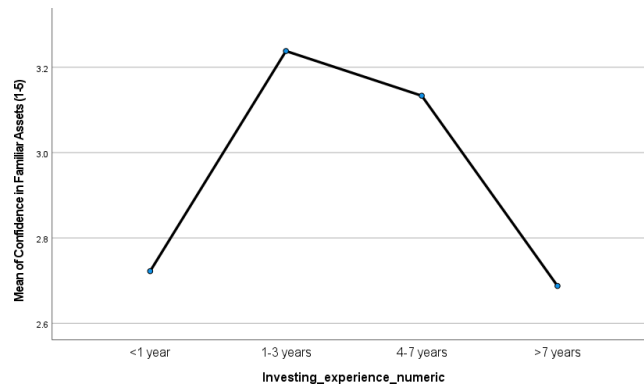
Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Confidence in Familiar Assets (1-5)	Based on Mean	.648	3	66	.587
	Based on Median	.341	3	66	.796
	Based on Median and with adjusted df	.341	3	62.016	.796
	Based on trimmed mean	.621	3	66	.604

ANOVA

Confidence in Familiar Assets (1-5)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.280	3	1.427	.781	.509
Within Groups	120.591	66	1.827		
Total	124.871	69			



Source: Own analysis using primary data

- A one-way ANOVA was conducted to examine whether the mean score for Confidence in Familiar Assets (1–5) differs significantly across different levels of Investing Experience (<1 year, 1–3 years, 4–7 years, >7 years).
- First, the test for homogeneity of variances using Levene's Test was non-significant ($p = 0.587$), indicating that the assumption of equal variances across groups was satisfied.
- The ANOVA results showed that the differences in mean Confidence scores across the groups were not statistically significant, $F(3, 66) = 0.781$, $p = 0.509$. This suggests that there are no meaningful differences in Confidence in Familiar Assets based on different levels of investing experience.
- The mean Confidence scores were:
 - <1 year: 2.72
 - 1–3 years: 3.24
 - 4–7 years: 3.13
 - 7 years: 2.69
- Although slight differences in mean scores were observed, they were not statistically significant.
- Since the p-value was greater than 0.05, the null hypothesis (H_0) is not rejected. Therefore, the mean Confidence in Familiar Assets does not significantly differ across different levels of Investing Experience.

Hypothesis 5–

Null Hypothesis (H_{05}): Investing Experience and Perceived Investment Skills Compared to Others do not significantly predict Confidence in Familiar Assets

Alternative Hypothesis (H_{A5}): Investing Experience and Perceived Investment Skills Compared to Others significantly predict an investor's Confidence in Familiar Assets.

Table 7: Investing Experience and Perceived Investment Skills Compared to Others significantly predict an investor's Confidence in Familiar Assets.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.032 ^a	.001	-.029	1.364	.001	.035	2	67	.966

a. Predictors: (Constant), Skills_numeric, Investing_experience_numeric

b. Dependent Variable: Confidence in Familiar Assets (1-5)

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.129	2	.065	.035	.966 ^b
	Residual	124.742	67	1.862		
	Total	124.871	69			

a. Dependent Variable: Confidence in Familiar Assets (1-5)

b. Predictors: (Constant), Skills_numeric, Investing_experience_numeric

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
Model		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.111	.608		5.114	.000		
	Investing_experience_numeric	-.026	.150	-.021	-.171	.865	.979	1.022
	Skills_numeric	-.045	.201	-.028	-.223	.824	.979	1.022

a. Dependent Variable: Confidence in Familiar Assets (1-5)

Source: Own analysis using primary data

- A linear regression analysis was conducted to investigate whether Investing Experience and Perceived Investment Skills Compared to Others significantly predict an investor's Confidence in Familiar Assets (rated from 1 to 5).
- The model summary indicated that the multiple correlation coefficient R was 0.032, and the coefficient of determination R^2 was 0.001. This suggests that only 0.1% of the variance in Confidence in Familiar Assets is explained by Investing Experience and Perceived Skills together, which is extremely low.
- The ANOVA table showed that the regression model was not statistically significant, $F(2, 67) = 0.035$, $p = 0.966$. Since the p -value is much greater than 0.05, it indicates that the model does not significantly predict the dependent variable.
- Looking at the coefficients table:
 - Investing Experience had a non-significant effect on Confidence ($B = -0.026$, $p = 0.865$).
 - Perceived Investment Skills also had a non-significant effect ($B = -0.045$, $p = 0.824$).
- Both independent variables had very high p -values (greater than 0.05), confirming that neither predictor has a statistically meaningful relationship with Confidence in Familiar Assets.
- Thus, the null hypothesis (H_0) is not rejected, and it is concluded that Investing Experience and Perceived Investment Skills Compared to Others do not significantly predict an investor's confidence in familiar assets.

Findings and Recommendations

Findings

Demographic Analysis

- Gender: The group was split evenly between men and women (both 41.43%), with a few identifying as "Other" (5.71%) or choosing not to say (11.43%). This mix gives a balanced view of investor perspectives.
- Age: Most participants were between 25–34 years old (30.36%), followed by 35–44 (28.57%) and 45–54 (23.21%). Younger (18–24) and older (55+) investors were

less common, at 17.86% and 16.67%, showing the focus was on working-age adults.

- Education: Many had advanced degrees (26.19% with a Master's or higher), while others had high school (20.24%), bachelor's (19.05%), or diploma (17.86%) qualifications. This suggests a fairly educated group, which might shape how they approach investing.
- Income: The biggest chunk earned less than ₹3,00,000 a year (38.57%), followed by ₹6,00,001–₹10,00,000 (22.86%), over ₹10,00,000 (20%), and ₹3,00,001–₹6,00,000 (18.57%). Lower incomes could mean less money to invest.
- Experience: Most had 1–3 years of investing experience (30%), followed by less than 1 year (25.71%), over 7 years (22.86%), and 4–7 years (21.43%). This shows a mix of beginners and seasoned investors.

Inferential Statistical Analysis

- Risk Preferences: Most investors (30 out of 70) took a middle-of-the-road approach to risk, preferring moderate strategies. About 24 were bold risk-takers, and 16 played it safe. This shows a range of comfort levels with risk.
- Following the Crowd: A good number (30 out of 70) said they don't follow the crowd at all, while 26 were very likely to go with the flow, and 14 were somewhat likely. This means some investors think independently, but others get swayed by what everyone else is doing.
- Media Influence: Opinions on media varied—28 relied on it heavily, 24 ignored it completely, and 18 used it a little. This shows investors get their info from different places.

Testing Our Ideas

We tested five ideas (hypotheses) to see if things like gender, age, or experience shaped investor behavior. Here's what we learned:

1. Gender and Risk: Gender didn't affect how risky or cautious investors were ($p = 0.409$). Men, women, and others had similar approaches to risk, which might surprise those who think gender plays a big role.

2. *Experience and Crowd-Following*: Whether someone was new or experienced didn't change how likely they were to follow the crowd ($p = 0.400$). Even seasoned investors can get caught up in trends.
3. *Age and Confidence*: Confidence in familiar investments (like stocks they know well) didn't vary much by age ($p = 0.577$). Younger and older investors felt similarly confident, with scores ranging from 2.70 (18–24 years) to 3.35 (25–34 years).
4. *Experience and Confidence*: Experience didn't make a big difference in confidence either ($p = 0.509$). Scores ranged from 2.69 (over 7 years) to 3.24 (1–3 years), but the differences weren't meaningful.
5. *Predicting Confidence*: Neither experience nor how skilled investors thought they were compared to others predicted their confidence in familiar investments ($p = 0.966$). These factors explained almost none of the confidence levels.

Recommendations

The following practical recommendations are suggested to help investors make better choices and avoid common pitfalls:

1. Learn About Your Biases:

- Set up workshops or online courses to teach investors about biases like following the crowd, being overly confident, or fearing losses too much. Since experience didn't reduce crowd-following, these should target everyone, from newbies to professionals.
- Use real-life examples, like stock market bubbles, to show why going with the crowd can backfire. Encourage investors to do their own research before jumping in.
- Teach people to question financial news and social media hype, since 40% lean heavily on media. Simple tips, like checking multiple sources, can help.

2. Get Tailored Advice:

- Financial advisors should figure out each client's comfort with risk (cautious, balanced, or bold) and build plans that match, since risk preferences vary but aren't tied to age or gender.
- Use quizzes to spot biases, like sticking to a stock's original price (anchoring) or trading too much (overconfidence). Advisors can suggest tricks, like setting strict sell points, to stay on track.

3. Use Smart Tech:

- Create apps that gently nudge investors to avoid mistakes, like selling winning stocks too soon or buying hyped-up ones without checking. A pop-up saying, “Have you researched this stock?” could make a difference.
- Offer tools that show how spreading investments (diversification) or sticking to a long-term plan can beat impulsive moves driven by news or overconfidence.

4. Support from Rules and Campaigns:

- India’s market regulator, SEBI, could require investment apps or brokers to show warnings about biases, like, “Beware of buying just because everyone else is.” This could calm investors during crazy market moments.
- Team up with colleges or community groups in Delhi NCR to teach young investors (18–24 years) about smart investing. They’re a small but growing group who could benefit from early habits.

5. Keep Studying:

- Do more studies over time to see how biases change as markets shift or investors gain experience. Exploring cultural or emotional factors could uncover why biases persist.
- Look at specific events, like market crashes, to see how they trigger biases in Delhi NCR investors.

CHAPTER 5

CONCLUSION

The journey through this research project, *How Behavioral Biases Shape Investment Choices*, has been an eye-opening exploration into the human side of financial decision-making. Conducted in the bustling region of Delhi NCR, this study set out to understand why retail investors sometimes make choices that don't align with cold, hard logic. By diving into the world of behavioral finance, we've uncovered how emotions, mental shortcuts, and social pressures can nudge investors away from the rational path laid out by traditional finance theories. The findings, drawn from a diverse group of 70 investors, offer valuable lessons and a call to action for anyone looking to make smarter financial moves.

This study basically says investors aren't cold, calculating robots who always nail the perfect choice. Traditional finance, with big ideas like the Efficient Market Hypothesis, acts like people are flawless at crunching data and always make moves to stack up cash. But come on, real life's way messier—fear, hype, or just wanting to roll with the crowd can totally trip people up and cost them big. That's where behavioral finance jumps in, showing the raw, human side of money decisions. It's like, biases—thinking you're hot factors, freaking out over losses, getting stuck on old prices, following the herd, or only hearing what you wanna hear—aren't just random. They're legit forces that mess with how investors deal with their dough.

This study zoomed in on five ways our brains totally mess with us when it comes to money. Overconfidence has investors acting like they're the market's boss, making wild bets or trading way too much. Loss aversion, linked to that “disposition effect” thing, is why people hold onto dud stocks but ditch winners too fast, scared of feeling dumb. Anchoring's like being stuck on some old number, like what you paid for a stock, and it distorts your thinking. Herd mentality's when everyone's chasing the same hot trend, pumping up bubbles or crashing hard. And confirmation bias? That's when you only listen to factors that supports what you already think, missing all the warning signs. Put 'em together, and these biases are like a big, complex trap that can wreck even the smartest money plans.

To get a clearer picture, we surveyed a varied group of Delhi NCR investors—men and

women in equal measure, mostly young to middle-aged, with incomes ranging from modest

to comfortable and investing experience from rookie to seasoned. Using a carefully designed questionnaire, we asked about their risk preferences, tendency to follow the crowd, and confidence in familiar investments. The data, crunched with tools like Excel and SPSS, revealed some surprising truths. While we expected factors like gender, age, or experience to strongly influence behaviors like risk-taking or crowd-following, the numbers told a different story. There was no significant link between gender and risk appetite, experience and herd behavior, or age/experience and confidence in known investments. Even how skilled people thought they were didn't predict their confidence. These findings suggest that biases might not always follow predictable patterns tied to demographics—they could depend more on the moment, the market, or other hidden factors.

Still, the survey painted a vivid picture of investor behavior. Nearly half preferred a balanced approach to risk, showing caution but not fear. Over a third of these investors said they're super likely to jump on market trends, which screams herd mentality kicking in. And 40% are glued to the media for advice, which can totally crank up confirmation bias when news just keeps feeding them what they already believe. These trends show that behavioral biases are definitely a thing for Delhi NCR investors, even if we can't pin down exactly why based on their age, gender, or how long they've been at it.

Alright, what's the big takeaway? Humans are super complex when it comes to financial decisions. These biases we looked at aren't just some nerdy theory—they're real, popping up when people freak out and sell during a market slump or pile into a hyped-up stock just 'cause everyone's doing it. They explain why markets can go nuts, ignoring the chill logic of old-school finance models. But here's the kicker: our data didn't show clear links to factors like age or gender, which tells us biases are tricky. They might spark in certain moments—like when the market's on fire or crashing hard—or get shaped by cultural vibes or personal quirks we haven't cracked yet. That's a green light for more digging, maybe by following investors over time or checking out how India's wild, fast-moving economy tweaks these behaviors.

The real deal here is that knowing your weak spots makes you stronger. This study isn't just about calling out where investors distort—it's about handing them a game plan to make smarter calls. Picture workshops or online classes that teach investors how to catch themselves before they chase the crowd or make a dumb move. Financial advisors could

get personal, tweaking plans to match how much risk someone's actually cool with, and use tricks to spot biases early—like obsessing over what a stock cost way back when. Apps could ping you with a quick “yo, you sure about this?” before you hit the trade button on a whim. Even regulators like SEBI could slap warnings on trading apps about getting sucked into hype trains. These aren't just pie-in-the-sky ideas—they're legit ways to help regular people build better portfolios and dodge classic traps.

At the end of the day, this research screams that investing's not just crunching numbers—it's about real people. The Delhi NCR crew we studied? They're not robot calculators; they're humans with dreams, worries, and weird quirks that drive their money choices. By owning that, we can build a financial world that's not only sharper but also feels more human. This study's a solid step in that direction, giving insights that can help investors in Delhi NCR—and way beyond—grab the reins of their financial future with clearer minds and steadier vibes.

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QUESTIONNAIRE

1.

What is your age group?

- ☐ 18–24
- ☐ 25–34
- ☐ 35–44
- ☐ 45–54
- ☐ 55 & Above

2. **Gender**

- ☐ Male
- ☐ Female
- ☐ Other
- ☐ Prefer not to say

3. **Education Level**

- ☐ High School
- ☐ Diploma
- ☐ Bachelor's
- ☐ Master's or Higher

4. **Annual Income**

- ☐ < ₹3,00,000
- ☐ ₹3,00,001 – ₹6,00,000
- ☐ ₹6,00,001 – ₹10,00,000
- ☐ ₹10,00,000

5. **Investing Experience**

- ☐ <1 year
- ☐ 1–3 years
- ☐ 4–7 years
- ☐ 7 years

6. **Primary Asset Class Invested In**

- ☐ Stocks
- ☐ Mutual Funds
- ☐ Bonds
- ☐ Real Estate
- ☐ Others

7. Trading/Investment Frequency

- **Very Frequently**
- **Regularly**

- Occasionally
 - Rarely
8. **Risk Attitude**
- Risk Seeking
 - Moderate
 - Conservative
9. **Do you rely on friends/family for investment decisions?**
- Not at all
 - A little
 - A lot
10. **Do you rely on media sources for investment decisions?**
- Not at all
 - A little
 - A lot
11. **How do you perceive your investment skills compared to others?**
- Better
 - Same
 - Worse
12. **How much does the original price (anchor) influence your buying/selling decisions?**
- No Impact
 - Moderate
 - High Impact
13. **What do you usually do after a 15% drop in your investment?**
- Sell
 - Hold
 - Buy More
14. **Do you tend to follow market trends or herd behavior?**
- Not at all
 - Slightly
 - Very Likely
15. **How confident are you in investing in familiar assets?**
- Scale: 1 to 5
16. **Do you look for confirming information when making decisions?**

- **Always**
- **Sometimes**
- **Never**

17. Do you get influenced by the way options are presented (framing effect)?

- **Yes**
- **No**
- **Not Sure**

18. How familiar are you with behavioral finance concepts?

- **Not Familiar**
- **Slightly Familiar**
- **Moderately Familiar**
- **Very Familiar**

19. How often do you try to counteract behavioral biases in your decisions?

- **Never**
- **Rarely**
- **Often**
- **Sometimes**
- **Always**

20. Do you believe that understanding behavioral biases improves investment decisions?

- **Yes, Definitely**
- **To some extent**
- **Not really**
- **No**

