Major Research Project

Behavioral Drivers of Consumer Investment Decisions: A Data-Driven Analysis

Submitted By

Aishwarya Kochhar

2K23/DMBA/07

Under The Guidance

Dr Yashdeep Singh

Assistant Professor



DELHI SCHOOL OF MANAGEMENT

Delhi Technological University

Bawana Road Delhi 110042

CERTIFICATE

This is to certify that Aishwarya Kochhar, 2k23/DMBA/021 has submitted the project dissertation report titled "Behavioral Drivers of Consumer Investment Decisions: A Data-Driven Analysis" in partial fulfillment of the requirements for the award of the degree of Master of Business Administration (MBA) from Delhi School of Management, Delhi Technological University, New Delhi during the academic year 2024-25.

Dr. Yashdeep Singh
Assistant Professor
Delhi School of Management,
Delhi Technological University

DECLARATION

I, Aishwarya Kochhar, a student of Delhi School of Management, Delhi Technological University, hereby declare that the project report titled "Behavioral Drivers of Consumer Investment Decisions: A Data-Driven Analysis" is the result of my independent research work carried out under the guidance of Dr. Yashdeep Singh, Assistant Professor, Delhi School of Management.

The data, analysis, and findings presented in this report are original and have not been submitted previously to any other institution or university for the award of any degree, diploma, or certificate. Wherever references from existing literature or secondary data have been used, they have been duly acknowledged.

This report is submitted in partial fulfillment of the requirements of the Master of Business Administration (MBA) program at Delhi Technological University.

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Lastly, I would like to extend my thanks to my family and friends for their unwavering support and belief in me throughout this journey.

EXECUTIVE SUMMARY

This research explores the impact of psychological biases on consumer investment behavior, analyzed through the dual lens of marketing and data analytics. Unlike classical financial models that assume individuals make rational and informed choices, this study acknowledges the reality that investment decisions are often influenced by **cognitive distortions and emotional reactions**. The focus is on identifying how common biases—such as **overconfidence, loss aversion, confirmation bias, familiarity bias, framing effects**, and **herding tendencies**—shape consumer preferences when selecting financial products.

To collect primary data, a structured survey was administered to over 200 participants representing a broad mix of demographic groups, including students, working professionals, and entrepreneurs. The questionnaire was designed to assess factors such as investment confidence, risk appetite, behavioral inclinations, and susceptibility to social influence. The collected responses were analyzed using **quantitative methods**, including descriptive statistics, cross-tabulation, and chi-square testing, to uncover relationships between demographic characteristics and decision-making patterns.

The findings indicate that **income levels play a critical role** in shaping risk preferences. Respondents in lower-income brackets tended to favor safer, more familiar investment options—such as established stocks—while higher-income participants exhibited greater willingness to take financial risks. Individuals who rated themselves highly in financial knowledge were more likely to display **overconfidence**, which sometimes resulted in uncalculated risk-taking. Additionally, **herding behavior** and **confirmation bias** were widely observed, suggesting that both social influence and belief reinforcement significantly affect consumer decision-making across demographic segments.

These insights offer valuable implications for marketers and product strategists, especially in the financial services sector. Recognizing these behavioral patterns can support **more effective segmentation, personalized messaging**, and improved engagement strategies. From an analytics standpoint, the study showcases how **behavioral data** can be used to anticipate consumer actions and enhance the design of **decision-support systems**.

In summary, this project connects the principles of behavioral science with practical marketing applications by applying **analytical tools to decode investor psychology**. It emphasizes the growing relevance of **behavioral segmentation, data-informed communication**, and **user-focused financial product design** in today's marketing and analytics-driven business environment.

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INTRODUCTION

1.1 Background

Traditional theories in economics and finance generally assume that individuals make decisions based on logic and complete information, aiming to maximize either utility or returns. The **Efficient Market Hypothesis (EMH)**, for instance, argues that asset prices always reflect all publicly available information, making it nearly impossible for investors to consistently outperform the market. Similarly, **Modern Portfolio Theory (MPT)** encourages rational diversification as a way to reduce risk while maximizing returns.

However, in reality, consumer decisions—especially in the context of financial products—often do not follow these rational frameworks. Instead, choices are shaped by **cognitive shortcuts, emotional reactions, and social dynamics**. These behavioral deviations from rationality have led to the emergence of **behavioral insights**, a multidisciplinary field that draws from psychology, marketing, and analytics to better understand how people actually make decisions, particularly in complex or high-stakes situations.

The Role of Cognitive Biases in Investment Choices

This study explores several core psychological biases that significantly affect how consumers assess and select investment options:

- **Familiarity Bias**: Consumers often favor financial instruments or brands they recognize, even when unfamiliar alternatives may offer better outcomes. This preference can lead to insufficient diversification and missed opportunities.

- **Overconfidence Bias**: Individuals frequently overrate their knowledge of financial matters, which can result in taking unnecessary risks or making hasty, ill-informed decisions.

- **Loss Aversion**: The pain associated with potential losses is generally felt more intensely than the satisfaction of potential gains. This emotional asymmetry often causes people to avoid risk or cling to underperforming assets.

- **Framing Effect**: The way investment choices are presented—highlighting either gains or losses—can greatly influence decision-making, even if the core facts remain constant.

- **Confirmation Bias**: People tend to seek out information that aligns with their existing beliefs and ignore contradictory evidence, which can reinforce poor financial habits and limit objective analysis.

Social Influences and Behavioral Patterns

In addition to internal cognitive biases, external **social influences** play a powerful role in how consumers make investment decisions. Input from **friends, family, media, and societal trends** often impacts choices more than objective data. This social pressure can lead to **herding behavior**, where individuals mimic the actions of others rather than relying on their own evaluation. Such patterns contribute to the formation of **market anomalies**, including speculative bubbles or abrupt sell-offs triggered by collective panic.

From a **marketing standpoint**, recognizing these behavioral tendencies allows brands and financial institutions to develop **targeted campaigns**, create behavior-based segments, and craft messaging that aligns with the emotional and psychological realities of their audiences. From an **analytics perspective**, identifying and modeling these patterns through survey data or behavioral tracking supports more accurate predictions and enhances the effectiveness of personalization strategies.

1.2 Problem Statement

Traditional investment theories often assume that individuals make decisions logically, using complete information to evaluate all available options. However, in real-world scenarios, consumer behavior frequently diverges from these rational expectations due to the influence of **psychological and emotional biases**. Cognitive distortions such as **overconfidence, loss aversion, herding tendencies**, and **framing effects** play a major role in how individuals assess investment opportunities and respond to changes in the market environment.

Although behavioral science has gained considerable traction in recent years, there remains a significant **gap in understanding how these biases differ across demographic categories** such as age, gender, and income level. Furthermore, many existing studies fall short in applying **quantitative and analytical techniques** to rigorously examine these behavioral patterns or to translate them into practical, data-backed insights.

This research aims to bridge that gap by employing a **data-driven analysis** to explore how behavioral biases affect investment preferences among different consumer groups. Through statistical examination of survey data, the study seeks to uncover patterns that can inform **marketing strategies, product development**, and **customer segmentation**. The ultimate goal is to enable businesses—particularly in the financial services sector—to align their offerings more closely with the actual behavioral tendencies of their target audience.

1.3 Objective of the Study

This study aims to investigate how behavioral insights and data analytics can be used to better understand consumer decision-making in the context of investment choices. The specific objectives are:

1. **To examine key behavioral biases influencing consumer investment behavior**: Identify prevalent cognitive biases such as overconfidence, loss aversion, familiarity bias, framing effects, and herding that shape consumer preferences.

2. **To evaluate the impact of emotional factors on investment choices**: Analyze how emotions like fear, confidence, and risk perception influence consumer responses, especially during market volatility or uncertainty.

3. **To analyze the relationship between consumer confidence and risk tolerance**: Assess how self-perceived financial knowledge correlates with willingness to take risks and investment decision-making behavior.

4. **To explore the influence of social and external factors on consumer decisions**: Understand the role of peers, media, influencers, and market trends in shaping consumer investment actions.

5. **To assess consumer decision-making under uncertainty**: Investigate how individuals make investment choices when faced with ambiguous or incomplete information, and what strategies they use to cope with risk.

6. **To uncover demographic patterns in investment behavior**: Use data analytics to compare consumer investment behavior across age, income, gender, and professional background, identifying distinct behavioral segments.

1.4 Scope of Study

This study focuses on understanding the behavioral factors that influence consumer decision-making in the context of personal investments. By integrating concepts from consumer psychology, behavioral economics, and data analytics, the research aims to uncover how cognitive and emotional biases shape consumer preferences for various investment options.

The scope of the study is defined as follows:

1. **Behavioral Focus**: The study examines key psychological biases—such as overconfidence, loss aversion, familiarity bias, confirmation bias, framing effects, and herding behavior—and their influence on consumer investment decisions.

2. **Consumer-Centric Perspective**: Rather than evaluating professional or institutional investors, the research is centered on individual consumers, especially young professionals, students, and retail investors.

3. **Demographic Segmentation**: The study analyzes how demographic variables such as age, gender, income level, and occupation impact behavioral biases and investment patterns.

4. **Geographical and Cultural Context**: The primary data has been collected from respondents within India, providing insights into the behavioral tendencies of Indian consumers in a culturally and economically diverse environment.

5. **Quantitative Analysis**: The research adopts a data-driven approach, utilizing statistical tools such as descriptive statistics, chi-square tests, and correlation analysis to uncover patterns and relationships in the data.

6. **Marketing and Analytics Application**: The findings are intended to inform marketers, financial service providers, and analysts about how behavioral segmentation and targeted messaging can improve product positioning, customer engagement, and

decision-support tools in the financial domain.

This study does not evaluate specific investment products or market performance, nor does it provide financial advice. Instead, its focus is on understanding consumer behavior through the lens of psychology and analytics to support better strategic decisions in marketing and financial services.

LITERATURE REVIEW

2.1 Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk

Kahneman and Tversky's groundbreaking work in 1979 introduced **Prospect Theory**, which became a cornerstone of behavioral economics. The theory challenged the classical **expected utility framework** by highlighting how individuals actually make decisions under uncertainty. Instead of evaluating outcomes purely rationally, people assess potential gains and losses relative to a reference point. One of the key ideas proposed is **loss aversion**—the tendency for individuals to experience the pain of losses more intensely than the pleasure of equivalent gains. They also identified **diminishing sensitivity**, where the perceived value of gains or losses diminishes as their magnitude increases.

Prospect Theory offers critical insights into how consumers approach investment decisions. It explains behavior such as the **reluctance to sell underperforming assets** or the avoidance of higher-risk, higher-return opportunities due to fear of loss. In the realm of **marketing and product design**, especially within financial services, this has important implications. Communicating product value in ways that **minimize perceived risk or emphasize security** is more effective with loss-averse audiences. Additionally, segmenting consumers based on their risk tolerance allows marketers to tailor messaging strategies that align with individual behavioral tendencies.

The insights drawn from Prospect Theory are highly applicable to the findings of this study. Survey responses revealed a significant preference for **low-risk, well-established investment options**, with many participants expressing strong sensitivity to potential losses. These behavioral patterns align closely with the predictions of Prospect Theory and serve as a theoretical foundation for interpreting investor behavior in a structured, data-driven way.

2.2 Shefrin, H. (2000). *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*

In *Beyond Greed and Fear*, Hersh Shefrin examines the psychological foundations that influence how individuals make investment decisions. He categorizes behavioral biases into two primary types: **cognitive biases**, such as overconfidence, anchoring, and hindsight bias; and **emotional biases**, including fear, regret aversion, and resistance to change. Shefrin argues that these mental shortcuts and emotional responses often lead individuals to stray from rational financial models, which can result in poor or inconsistent decision-making.

The book also explores how these individual biases collectively impact market behavior. For example, investors who are overly confident in their abilities may engage in frequent trading, while those driven by regret aversion may retain underperforming assets to avoid confronting losses. Additionally, **herding behavior**, or the tendency to follow the majority, amplifies these irrational patterns and can contribute to broader market disruptions such as speculative bubbles or sudden crashes.

Shefrin's work has had a lasting influence on the field of **behavioral finance**, offering a structured approach to recognizing and mitigating the effects of biases in investment contexts. It provides valuable insights not only for financial professionals but also for marketers and product developers seeking to understand how **psychological factors influence consumer preferences** and decision-making under uncertainty. The book's practical frameworks have increasingly informed **behaviorally driven marketing strategies**, emphasizing the importance of aligning product communication with real-world investor behavior.

2.3 Thaler, R. H. (1999). *Mental Accounting Matters*

Richard Thaler's concept of **mental accounting** examines the way individuals assign monetary value and purpose based on psychological rather than economic reasoning. Rather than viewing money as interchangeable, people mentally divide their finances into distinct "accounts" depending on factors such as the source of the money (e.g., salary vs. bonus) or its intended purpose (e.g., essentials, leisure, or investments). This tendency to compartmentalize can lead to **suboptimal financial choices**, such as spending windfall income carelessly or hesitating to reallocate funds between categories, even when it would be financially advantageous.

Mental accounting also brings attention to the **influence of framing** in the decision-making process. The way choices are presented—whether emphasizing a guaranteed return or a potential gain—can significantly affect how appealing an investment appears. For example, people often favor options framed as "secure" or "certain," even when alternatives might offer better expected returns but are perceived as riskier due to their variability.

Thaler's mental accounting framework has had a profound impact beyond behavioral economics, extending into **marketing and consumer psychology**. Marketers and financial product developers use this understanding to craft messages and offerings that align with how customers instinctively evaluate financial options. For instance, consumers might be more loyal to financial products that feel familiar or are perceived as "safe," even if they deliver lower returns. The theory also helps explain preferences for **low-risk investments**, resistance to change, and certain patterns of brand attachment in financial decision-making.

2.4 Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance

In his 2003 publication, Robert Shiller offers a pointed critique of the **Efficient Market Hypothesis (EMH)** and contributes significantly to the development of **behavioral finance**. He challenges the idea that asset prices always reflect all available information, suggesting instead that markets are often influenced by **investor emotions, social behavior, and psychological factors**. To describe this phenomenon, he coined the term **"irrational exuberance,"** capturing how emotional overreactions can inflate asset prices far beyond their actual value, often culminating in market bubbles and abrupt crashes.

Shiller's work places strong emphasis on **social dynamics** in the investment landscape. He discusses how behaviors such as **herding, emotional contagion, and overreaction to news** tend to override logical decision-making. These behaviors contribute to **market inefficiencies**, undermining the core assumptions of EMH which rely on the notion of rational, self-correcting markets.

The insights from Shiller's research have been instrumental in reshaping how both scholars and practitioners view financial markets. His recognition of the **impact of sentiment and group behavior** has led to new approaches in economic theory and financial strategy. Furthermore, his findings have influenced how financial products are **marketed and communicated**, highlighting the necessity of designing product messaging that takes into account the **psychological tendencies and biases** of consumers.

2.5 Statman, M. (2019). Behavioral Finance: The Second Generation

In *Behavioral Finance: The Second Generation*, Meir Statman offers a transformative view of financial decision-making by expanding the focus from isolated behavioral biases to a comprehensive understanding of how individuals make choices based on emotional, psychological, and social motivations. Unlike the traditional assumption that investors always strive to maximize financial returns, Statman asserts that people often aim for **broader life goals** such as emotional security, personal happiness, social acceptance, and identity expression.

Statman challenges the classical economic model of "rationality" by redefining it through what he calls **"normal behavior"**—actions that may not fit within the confines of rational choice theory but are entirely logical when seen through the lens of personal values and life aspirations. He introduces the concept of **behavioral portfolios**, where individuals mentally assign money to distinct categories or purposes—such as long-term safety, ambitious goals, or lifestyle enjoyment—rather than treating all financial assets as part of a single return-maximizing plan.

This perspective significantly influences how financial services should be marketed, communicated, and personalized. It encourages marketers and financial advisors to consider not just **demographic characteristics**, but also **emotional and psychological profiles** when segmenting audiences or recommending products. By recognizing that consumers attach **emotional meaning** to their investments, financial professionals can tailor strategies that align with clients' inner motivations and desired life outcomes.

Statman's work also reinforces the importance of empathetic financial planning, where understanding the **non-financial drivers** behind consumer behavior becomes key to building trust, loyalty, and satisfaction. It offers a powerful framework for designing **behaviorally aware marketing campaigns and tools** that support real people making real-life decisions—not just economic agents responding to data.

2.6 Nofsinger, J. R. (2017). The Psychology of Investing (6th ed.)

In *The Psychology of Investing*, John R. Nofsinger presents an in-depth exploration of the mental and emotional patterns that shape investor decision-making. The book addresses a broad spectrum of psychological biases such as **anchoring**, **availability heuristics**, **representativeness**, **regret aversion**, and **herding behavior**, and illustrates their effects through real-world examples and case studies. Nofsinger argues that investment decisions are rarely made with complete rationality; rather, they are often influenced by emotional responses, mental shortcuts, and the behavior of others.

What sets this work apart is its **practical application of theory**. Nofsinger links psychological concepts to common investor behaviors, showing how biases can lead to repeated errors like **overtrading, performance chasing**, and **ineffective diversification**. He also delves into how individuals react during periods of market instability—highlighting tendencies such as **panic-driven selling** or retreating to safer assets in times of uncertainty.

This book offers a meaningful contribution to understanding the behavioral foundations of investment activity. Its accessible structure and practical orientation make it especially useful not only for academic purposes but also for professionals who aim to design investment strategies, platforms, or marketing campaigns that align with human behavior. Nofsinger's insights support the growing trend of incorporating **behavioral principles into financial planning, client risk assessment**, and **investor communications**, enabling more empathetic and effective engagement with consumers.

RESEARCH METHODOLOGY

3.1 Research Design

The study follows a quantitative research approach using a structured questionnaire to collect data on investment behavior and psychological biases influencing financial decisions.

3.2 Population and Sample

The target population for this study comprises individual investors and potential investors with varying levels of financial knowledge and investment experience. This includes individuals from different demographic backgrounds—such as age, gender, income level, and profession—who are capable of making independent investment decisions or have shown interest in personal finance and investment options.

To gather relevant data for analysis, a **convenience sampling** technique was employed. The sample consisted of **207 respondents**, selected based on their accessibility and willingness to participate in the study. The participants were approached via online platforms, personal networks, and digital survey circulation, allowing for diverse participation within a limited timeframe.

The sample included a mix of **students, salaried employees, business owners, freelancers, homemakers, and retirees**. A significant proportion of respondents belonged to the **18–25 age group**, with a majority identifying as **students** or **young professionals**. Income levels varied, with the highest representation in the **less than ₹5 lakhs annual income bracket**. The gender distribution skewed slightly toward male respondents.

This heterogeneous sample enabled the study to examine behavioral biases across various demographic segments. While the convenience sampling method may limit the generalizability of findings to the broader population, the collected data provided valuable insights into the **relationship between demographic characteristics and behavioral tendencies** such as overconfidence, risk aversion, familiarity bias, and herding behavior in investment decisions.

3.3 Data Collection Methods

A survey was conducted among a diverse group of respondents, including students, working professionals, and investors, to understand their financial decision-making patterns. The questionnaire was designed to evaluate various behavioral finance aspects such as risk tolerance, influence of social factors, cognitive biases, and emotional responses to market changes.

3.4 Survey Structure

The questionnaire covered the following key areas:

- Demographic Information: Age, gender, profession, and income level.
- Investment Confidence: Self-assessment of financial knowledge and confidence in investment decisions.
- Risk Appetite and Loss Aversion: Preferences between safe and high-risk investments.
- Market Influence: Impact of media, friends, and trends on investment choices.
- Behavioral Biases: Questions assessing loss aversion, herd mentality, overconfidence, and confirmation bias.
- Decision-Making Patterns: Reactions to market downturns and tendency to follow advice without personal research.

3.5 Sampling Technique

The study employed a **convenience sampling method**, which involves selecting participants who are easily accessible and willing to respond. This non-probability sampling technique was chosen due to its practicality and efficiency in collecting data within a limited time frame.

The sample targeted individuals with **diverse levels of financial experience**, including students, working professionals, entrepreneurs, homemakers, and retirees. The aim was to capture a broad spectrum of investment behaviors and psychological patterns across various demographic segments.

A total of **207 valid responses** were obtained through the survey, providing a substantial dataset for statistical analysis. While the sampling method may limit the generalizability of the findings to the entire population, the diversity within the sample helped ensure that the data reflected a wide range of behavioral tendencies and investment decision-making styles.

This approach enabled the study to explore the influence of behavioral biases across multiple consumer segments and demographic variables, contributing to the depth and applicability of the research outcomes.

3.6 Data Analysis

- Descriptive Statistics: Frequency distribution and percentage analysis of responses.
- Comparative Analysis: Evaluating differences in biases across demographic groups.
- Correlation Analysis: Identifying relationships between confidence levels, risk tolerance, and investment biases.
- Behavioral Patterns Identification: Categorizing investors based on their responses and common trends observed.

ANALYSIS, DISCUSSION AND RECOMMENDATIONS

4.1 Findings

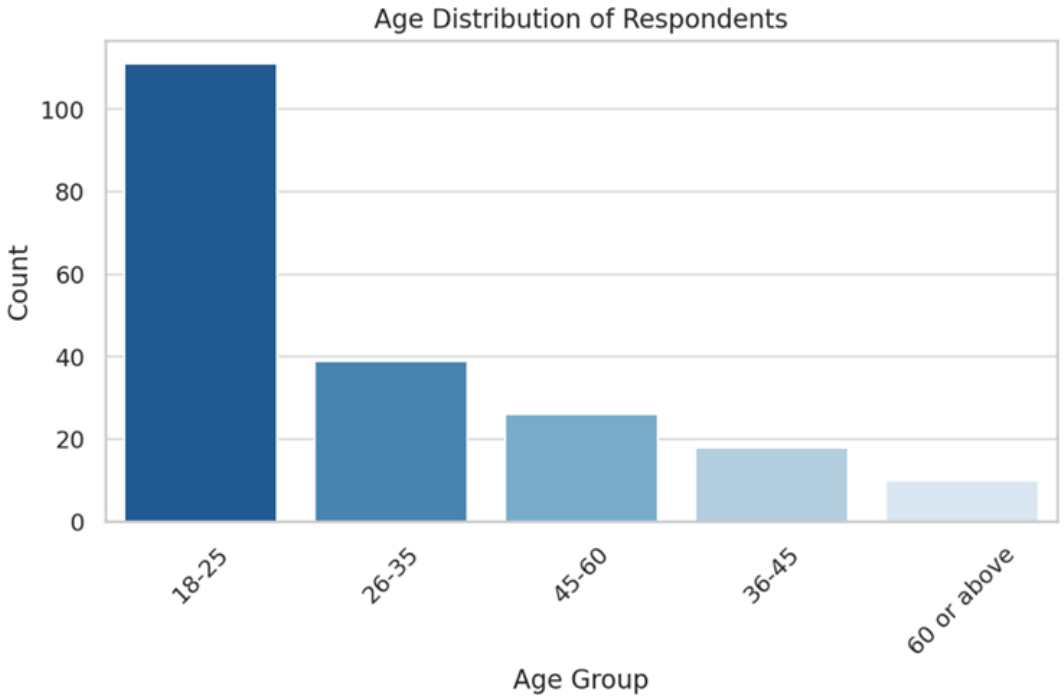


Figure 4.1: Age Distribution of Respondents

From the age distribution chart, the majority of respondents fall in the 18-25 age group, followed by 26-35, while older age groups (36-45, 45-60, and 60+) have fewer participants**.**

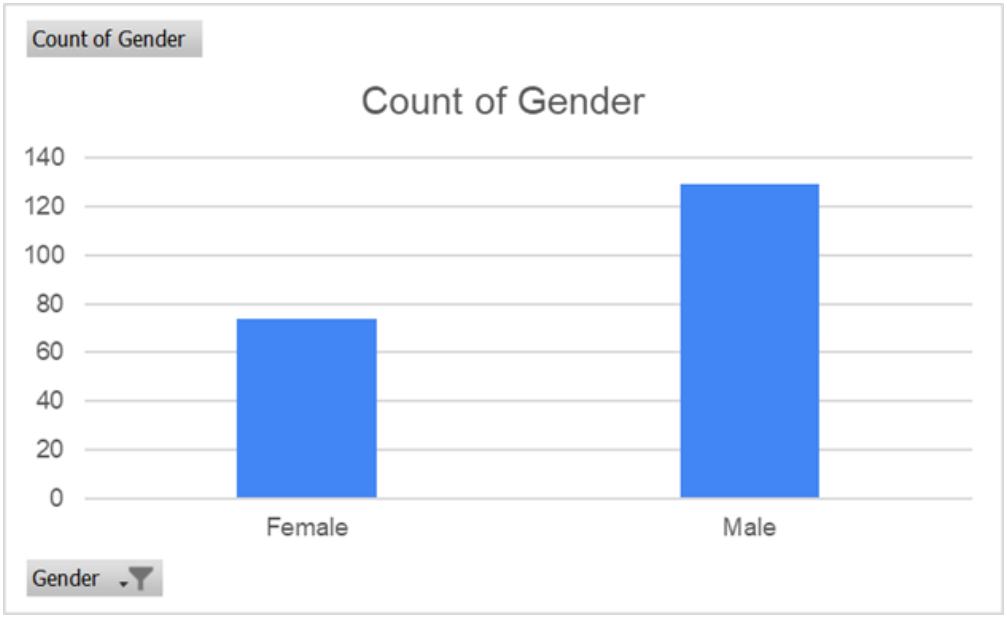


Figure 4.2: Count of Gender

The chart shows a higher number of male respondents compared to female respondents.

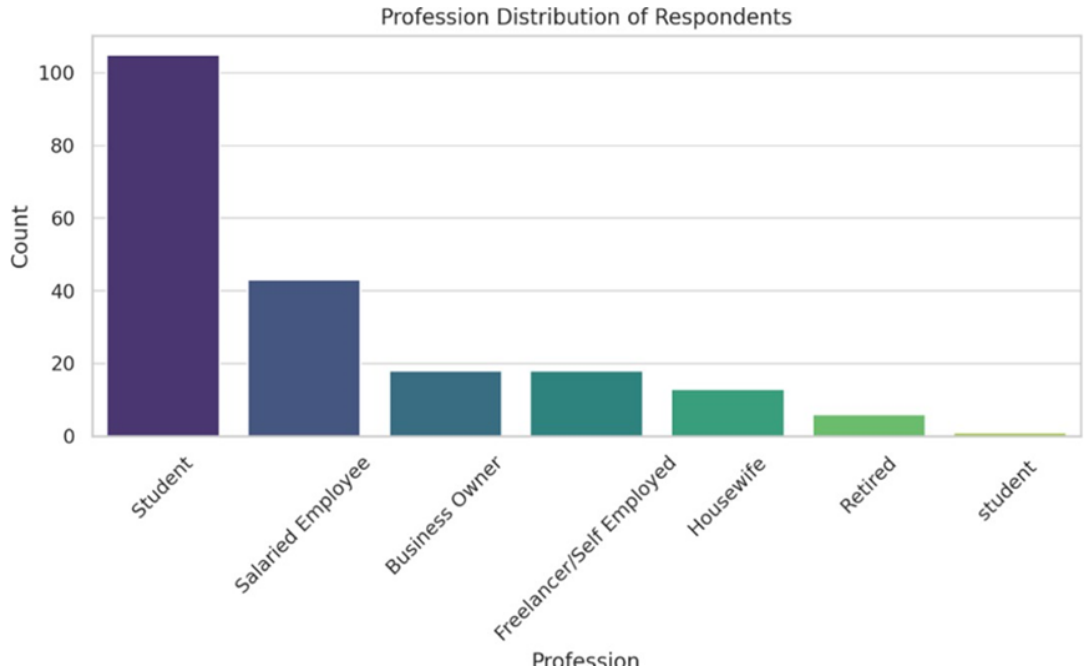


Figure 4.3: Profession Distribution of Respondents

The chart shows that the majority of respondents are **students**, followed by **salaried employees**, with fewer respondents from categories like **business owners, freelancers, housewives, and retired individuals**

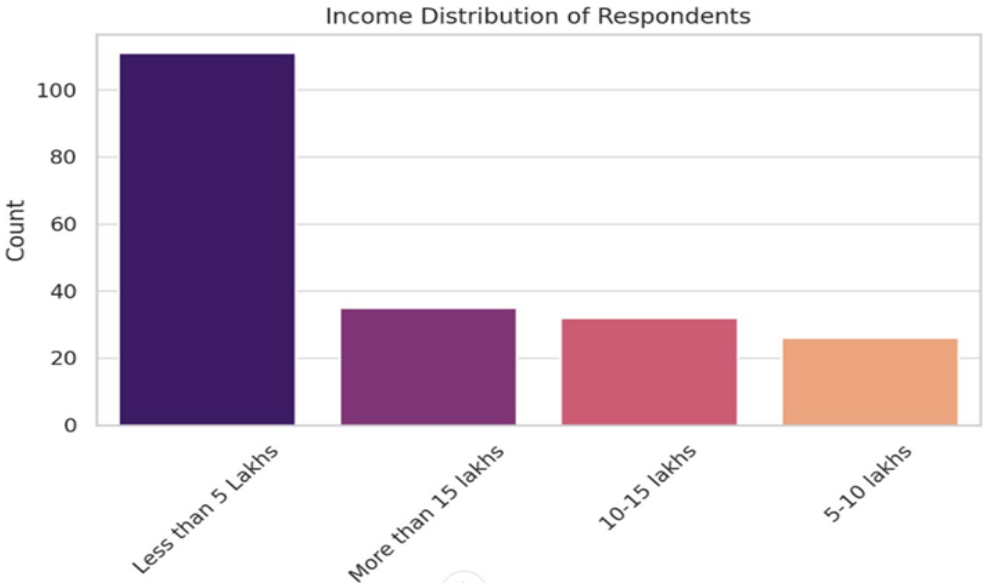


Figure 4.4: Income Distribution of Respondents

The chart indicates that most respondents have an income of less than 5 lakhs, while fewer respondents fall into higher income categories (5-10 lakhs, 10-15 lakhs, and more than 15 lakhs).

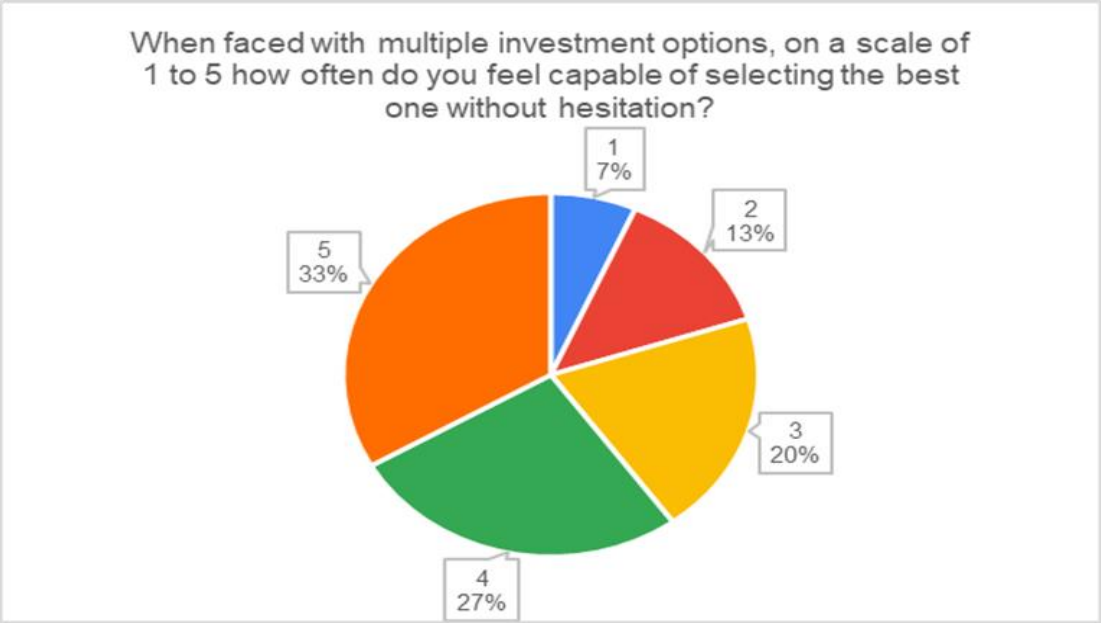


Figure 4.5:(Own Analysis)

High Confidence (Scores 4 & 5 - 60%)

- 33% of respondents rated themselves at **5**, indicating a strong sense of confidence in selecting the best investment.
- 27% rated themselves at **4**, suggesting they are fairly confident but may have occasional doubts.
- Together, these two categories show that **60% of participants feel confident in their investment decision-making abilities**.

Moderate Confidence (Score 3 - 20%)

- 20% of respondents selected **3**, reflecting a balanced approach where they neither feel extremely confident nor completely hesitant.
- This suggests a group of investors who may need further research or guidance before making investment choices.

Low Confidence (Scores 1 & 2 - 20%)

- 13% chose **2**, indicating mild uncertainty in selecting the right investment.
- 7% selected **1**, representing a very low level of confidence and high hesitation in making investment decisions.
- The combined 20% suggests that a portion of investors lacks confidence and may rely on external advice, peer influence, or further research before investing.

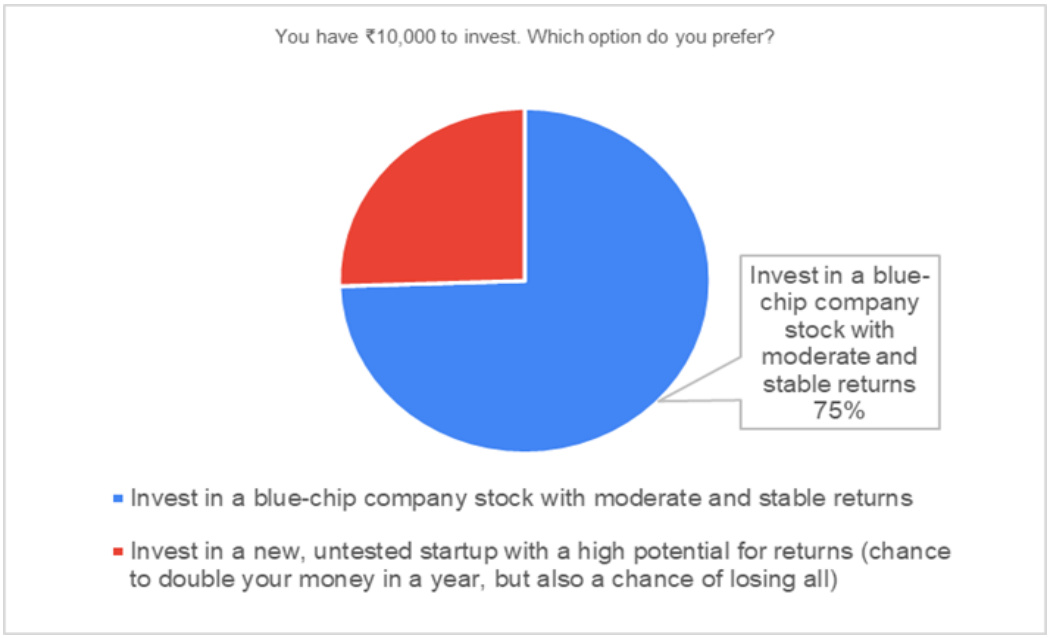


Figure 4.6: (Own Analysis)

- 75% of respondents prefer investing in a blue-chip company stock, which offers moderate and stable returns.

- 25% prefer investing in a new, untested startup, which has high potential returns but also a significant risk of losing all their money.

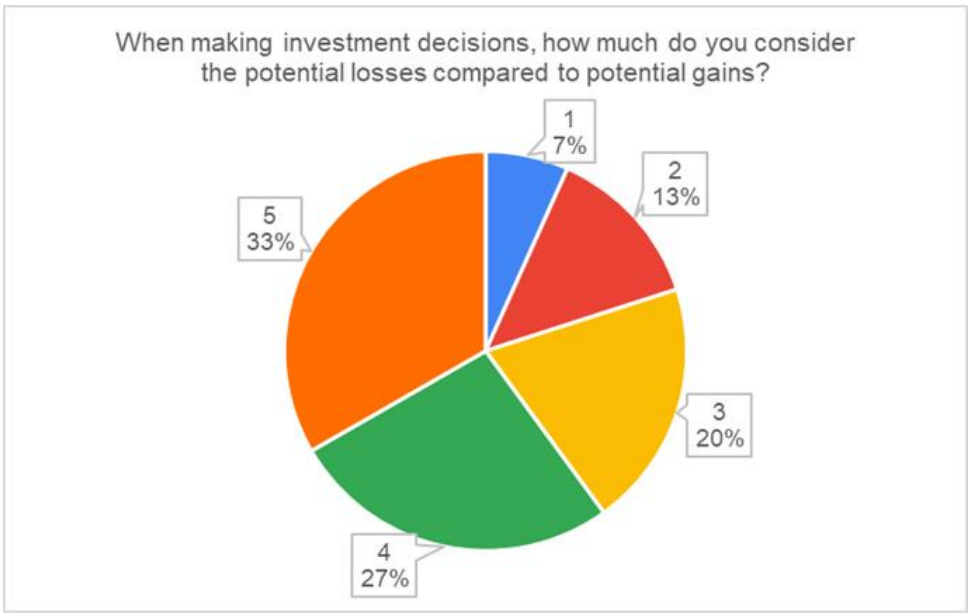


Figure 4.6:(Own Analysis)

High Loss Consideration (Scores 4 & 5 - 60%)

- 33% of respondents rated themselves at **5**, meaning they strongly consider potential losses before making an investment.
- 27% rated **4**, indicating a significant focus on risk evaluation.
- This suggests that **most investors are risk-conscious and prioritize protecting their investments**.

Moderate Consideration (Score 3 - 20%)

- These respondents maintain a **balanced approach** between risk and reward.

Low Loss Consideration (Scores 1 & 2 - 20%)

- 7% of respondents selected **1**, meaning they rarely consider losses before investing.
- 13% selected **2**, indicating a **low-risk aversion** mindset.
- These investors may be more inclined towards risk-taking and focusing on **potential gains rather than mitigating losses**.

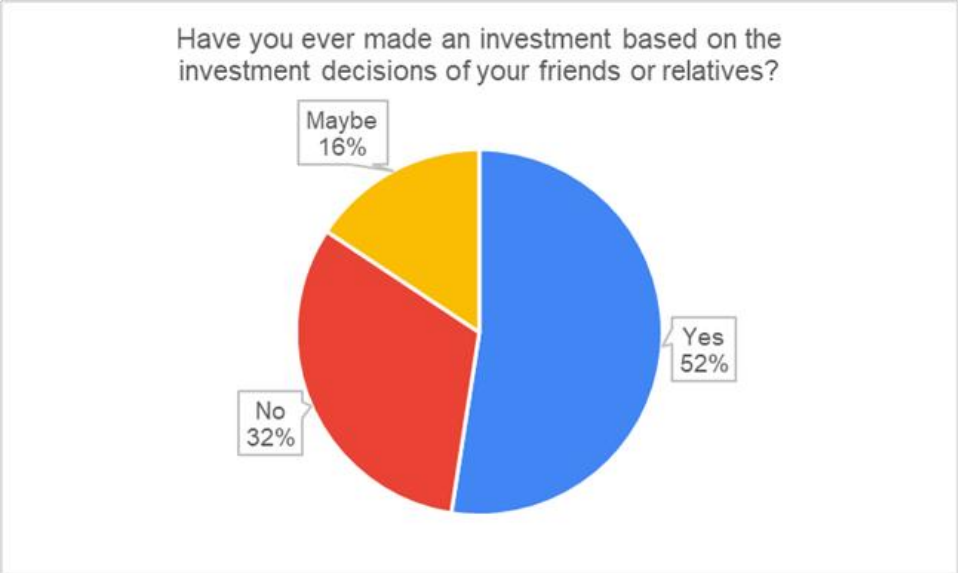


Figure 4.7:(Own Analysis)

- **52% of respondents answered "Yes"**, meaning they have followed the investment choices of friends or relatives.
- **32% answered "No"**, suggesting they make independent investment decisions.
- **16% answered "Maybe"**, indicating some level of social influence but not always.

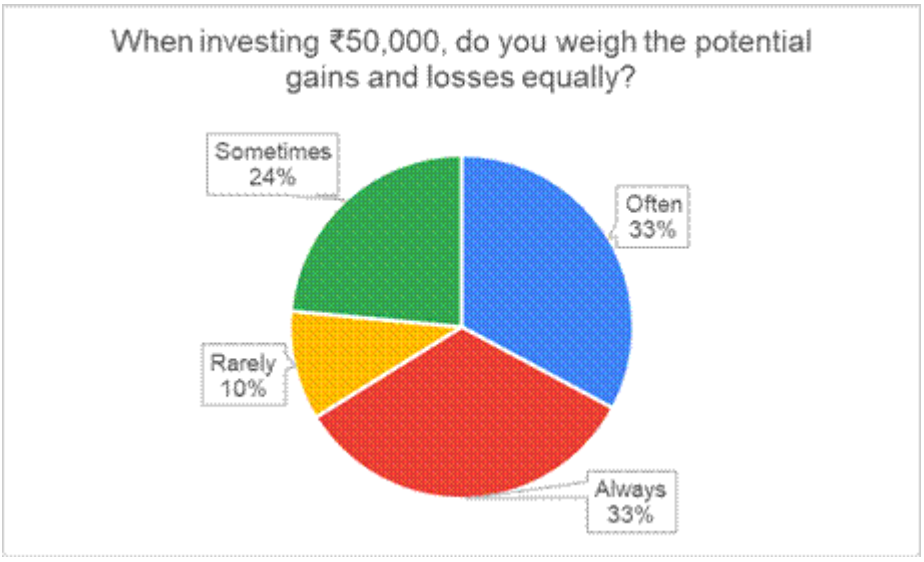


Figure 4.8:(Own Analysis)

- 66% of investors (Always + Often) actively assess risks and returns, indicating a

rational and cautious approach to investing.

- **24% (Sometimes) may consider gains and losses inconsistently,** potentially influenced by emotions or market trends.

- **10% (Rarely) suggests that some investors prioritize either profits or losses without a balanced approach,** which could lead to **impulsive or high-risk decisions**.

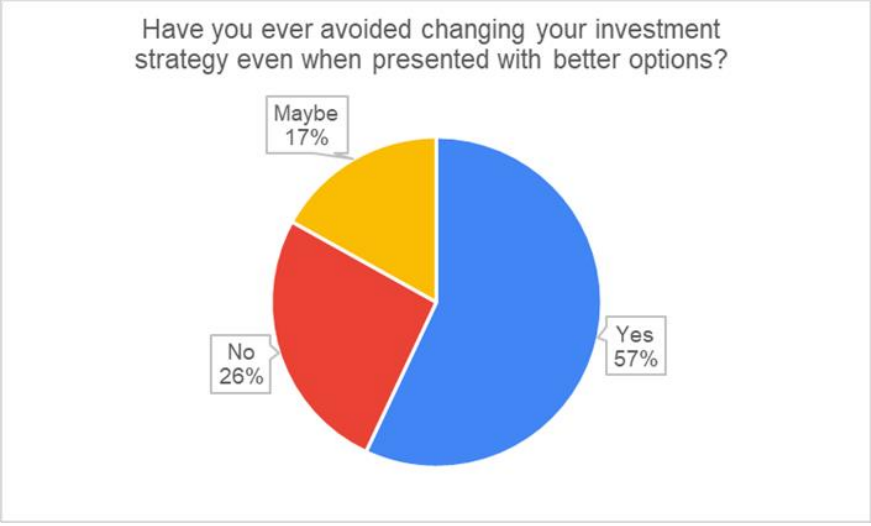


Figure 4.9:(Own Analysis)

- **57% of respondents answered "Yes"**, indicating that they resist changing their investment strategy even when better alternatives are available.

- **26% answered "No"**, meaning they are open to modifying their investment approach when new opportunities arise.

- **17% responded with "Maybe"**, suggesting uncertainty or occasional resistance to change.

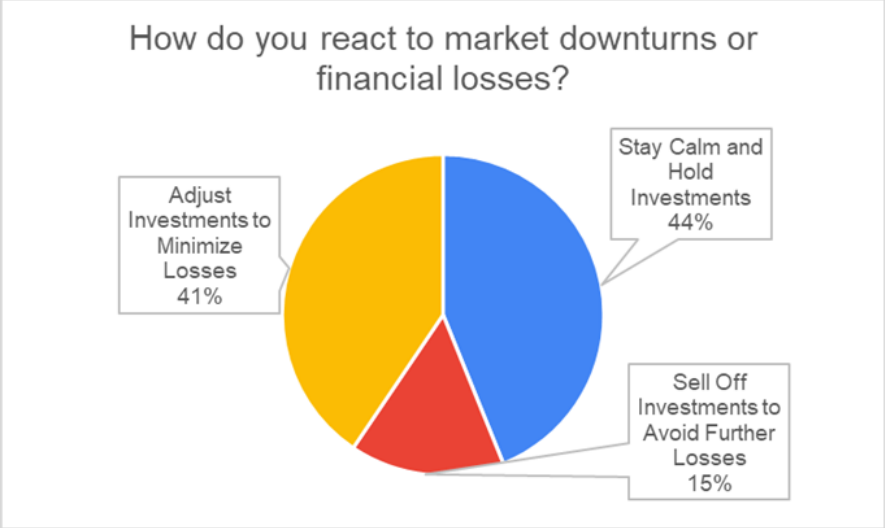


Figure 4.10:(Own Analysis)

- **44% of respondents "Stay Calm and Hold Investments"**, meaning they believe in long-term investment strategies and avoid panic selling.

- **41% "Adjust Investments to Minimize Losses"**, suggesting they take an **active approach to risk management**.

- **15% "Sell Off Investments to Avoid Further Losses"**, meaning they **exit the market quickly to cut their losses**.

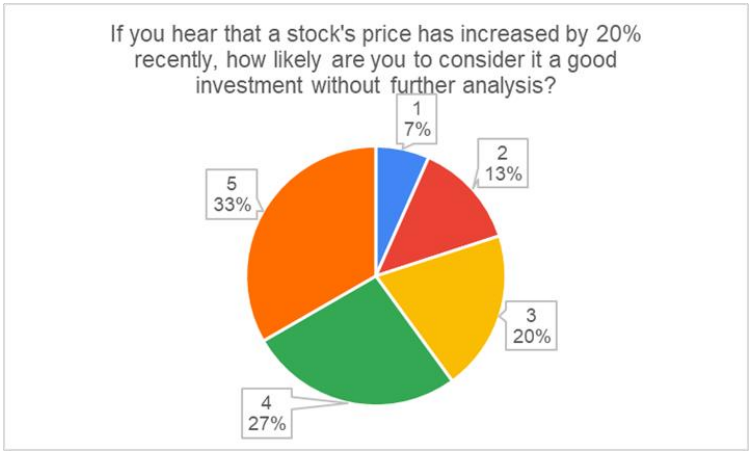


Figure 4.11:(Own Analysis)

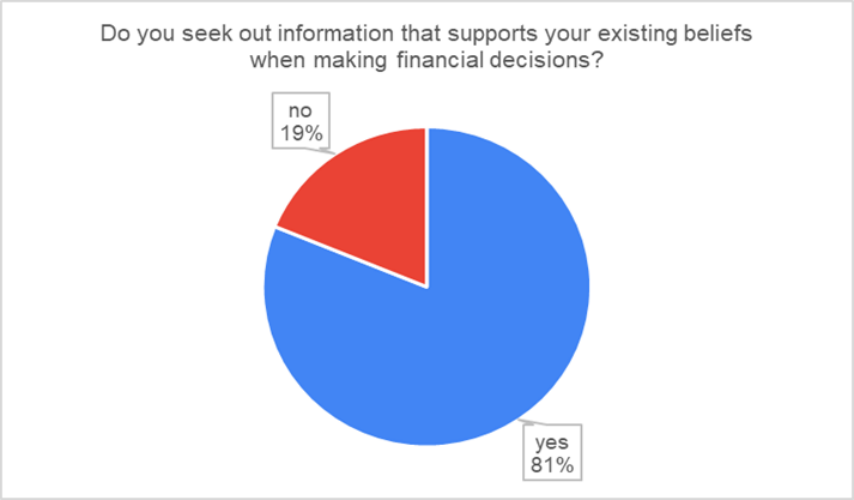


Figure 4.12(Own Analysis)

- 81% of respondents admit to seeking information that aligns with their existing beliefs.
- 19% actively look for opposing or diverse perspectives.

4.2 Analysis

Analysis of Investment Confidence and Risk Appetite

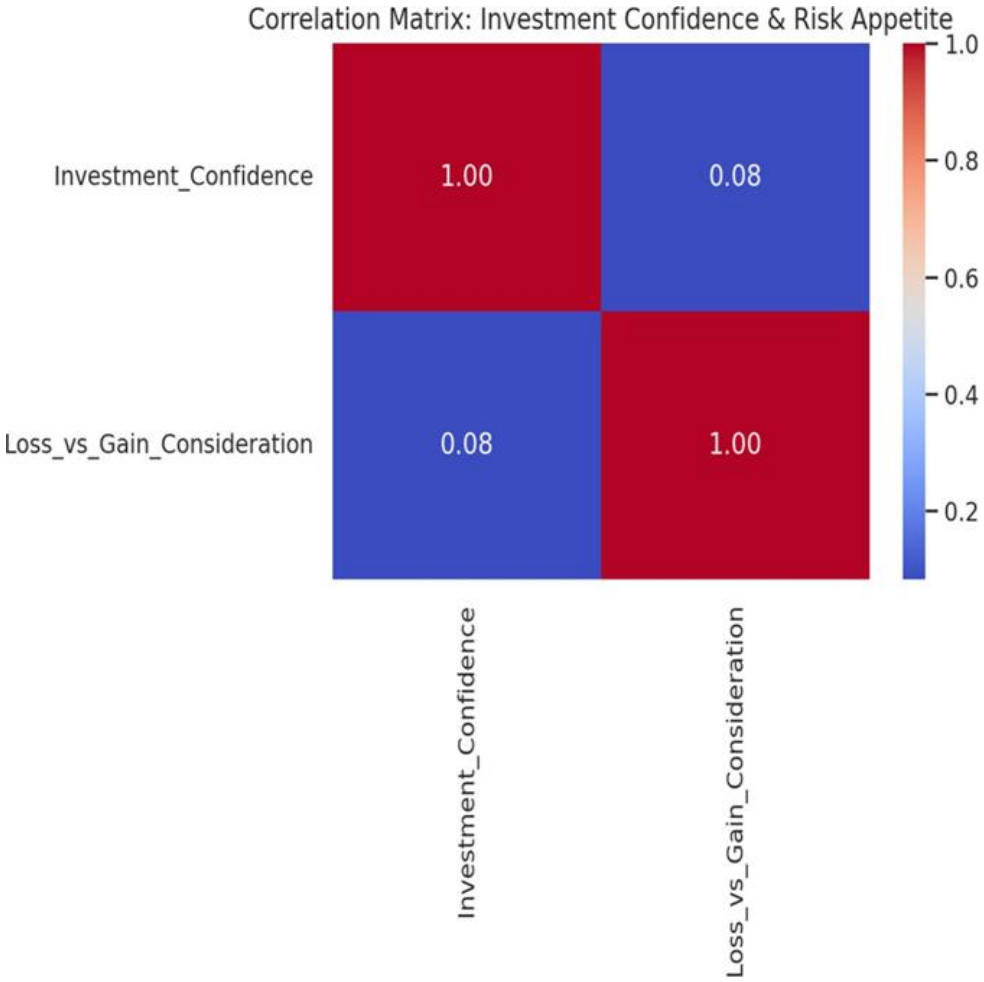


Figure 4.13:(Own Analysis)

The heatmap shows a weak positive correlation (0.08) between Investment Confidence and Loss vs. Gain Consideration (Risk Appetite).

This suggests that an investor's confidence level has minimal impact on their willingness to take risks.

1. **Understanding whether user investment behavior in FD or MF is dependent on Income Level and Age**

- **Relationship Between Investment Choice and Age**

Crosstab

Expected Count

		Age					
		18-25	26-35	36-45	45-60	60 or above	Total
Ifgivenachoicebetweenafixeddeposit FDoffering6annua		.5	.2	.1	.1	.0	1.0
	Fixed Deposit	34.9	12.1	5.9	8.0	3.1	64.0
	Mutual Fund	73.1	25.2	12.3	16.8	6.5	134.0
	No Preference	4.4	1.5	.7	1.0	.4	8.0
Total		113.0	39.0	19.0	26.0	10.0	207.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	12.321[a]	12	.420
Likelihood Ratio	12.385	12	.415
N of Valid Cases	207		

a. 11 cells (55.0%) have expected count less than 5. The minimum expected count is .05.

Figure 4.14:(Own Analysis)

- **Chi-Square Value**: 12.321
- **Degrees of Freedom (df)**: 12
- **p-value (Asymptotic Significance, 2-sided)**: 0.420

The p-value (0.420) is **greater than 0.05**, meaning there is **no statistically significant relationship** between age and investment choice. This suggests that the choice between Fixed Deposits and Mutual Funds **does not significantly differ** across age groups. The expected count table also shows that the distribution of choices remains relatively balanced across different age groups.

- **Relationship Between Investment Choice and Income Level**

Crosstab

Expected Count

		AnnualIncome				
		10-15 lakhs	5-10 lakhs	Less than 5 Lakhs	More than 15 lakhs	Total
IfgivenachoicebetweenafixeddepositFDoffering6annua		.2	.1	.5	.2	1.0
	Fixed Deposit	10.2	8.0	34.3	11.4	64.0
	Mutual Fund	21.4	16.8	71.9	24.0	134.0
	No Preference	1.3	1.0	4.3	1.4	8.0
Total		33.0	26.0	111.0	37.0	207.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	3.167[a]	9	.957
Likelihood Ratio	4.787	9	.853
N of Valid Cases	207		

a. 8 cells (50.0%) have expected count less than 5. The minimum expected count is .13.

Figure 4.15:(Own Analysis)

- **Chi-Square Value**: 3.167
- **Degrees of Freedom (df)**: 9
- **p-value (Asymptotic Significance, 2-sided)**: 0.957

The p-value (0.957) is **much greater than 0.05**, indicating that **investment choice is not significantly influenced by income level**. This means that people across different income brackets do not show **statistically significant differences** in their preference for FDs or MFs. The expected count table reinforces this, as investment choices seem proportionate across income levels.

2. Risk Aversion and Familiarity Bias based on Income Level, Age and

Gender

- **Gender-Based Bias**

Crosstab

Expected Count

		Gender		
		Female	Male	Total
Youhave10000toinvest. Whichoptiondoyouprefer	Invest in a blue-chip company stock with moderate and stable returns	55.4	97.6	153.0
	Invest in a new, untested startup with a high potential for returns (chance to double your money in a year, but also a chance of losing all)	19.6	34.4	54.0
Total		75.0	132.0	207.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.035[a]	1	.852		
Continuity Correction[b]	.000	1	.983		
Likelihood Ratio	.035	1	.852		
Fisher's Exact Test				1.000	.494
N of Valid Cases	207				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 19.57.

b. Computed only for a 2x2 table

Figure 4.16:(Own Analysis)

- **Pearson Chi-Square Value:** 0.035
- **Degrees of Freedom (df):** 1
- **Asymptotic Significance (p-value):** 0.852

Since the p-value (0.852) is much greater than 0.05, we fail to reject the null hypothesis. This means that there is no statistically significant relationship between gender and investment preference (blue-chip stocks vs. startups). Both males and females exhibit similar familiarity bias tendencies.

- **Age-Based Bias**

Crosstab

Expected Count

		Age					
		18-25	26-35	36-45	45-60	60 or above	Total
Youhave10000toinvest. Whichoptiondoyouprefer	Invest in a blue-chip company stock with moderate and stable returns	83.5	28.8	14.0	19.2	7.4	153.0
	Invest in a new, untested startup with a high potential for returns (chance to double your money in a year, but also a chance of losing all)	29.5	10.2	5.0	6.8	2.6	54.0
Total		113.0	39.0	19.0	26.0	10.0	207.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	7.685[a]	4	.104
Likelihood Ratio	9.919	4	.042
N of Valid Cases	207		

a. 2 cells (20.0%) have expected count less than 5. The minimum expected count is 2.61.

Figure 4.17:(Own Analysis)

- **Pearson Chi-Square Value: 7.685**
- **Degrees of Freedom (df): 4**
- **Asymptotic Significance (p-value): 0.104**

The p-value (0.104) is above 0.05, indicating no strong statistical evidence that investment preference varies significantly across age groups. While younger individuals (18-25) seem to prefer blue-chip stocks over startups, the differences across age groups are not statistically significant.

- **Income-Based Bias**

Crosstab

Expected Count

		AnnualIncome				
		10-15 lakhs	5-10 lakhs	Less than 5 Lakhs	More than 15 lakhs	Total
Youhave10000toinvest. Whichoptiondoyouprefer	Invest in a blue-chip company stock with moderate and stable returns	24.4	19.2	82.0	27.3	153.0
	Invest in a new, untested startup with a high potential for returns (chance to double your money in a year, but also a chance of losing all)	8.6	6.8	29.0	9.7	54.0
Total		33.0	26.0	111.0	37.0	207.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	14.872[a]	3	.002
Likelihood Ratio	13.982	3	.003
N of Valid Cases	207		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 6.78.

Figure 4.18:(Own Analysis)

- **Pearson Chi-Square Value: 14.872**
- **Degrees of Freedom (df): 3**
- **Asymptotic Significance (p-value): 0.002**

Since the p-value (0.002) is less than 0.05, we reject the null hypothesis. This means that income level has a significant impact on investment preference. Individuals with lower income (<5 lakhs) show a stronger preference for blue-chip stocks, whereas those with higher incomes (>15 lakhs) are more willing to take risks and invest in startups. This supports the idea that higher-income investors prefer riskier investments, while lower-income groups prefer safer options i.e have Familiarity Bias

4. Overconfidence Bias based on Confidence Level

Independent Samples Test

	Levene's Test for Equality of Variances		t-test for Equality of Means							
					Significance				95% Confidence Interval of the Difference	
	F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Equal variances assumed	.005	.942	-1.851	205	.033	.066	-.328	.177	-.677	.021
Equal variances not assumed			-1.860	93.773	.033	.066	-.328	.176	-.678	.022

Figure 4.18:(Own Analysis)

Since p-value = 0.0661 (> 0.05), There is no statistically significant difference in confidence levels between investors choosing blue-chip stocks vs. high-risk startups.

However, since it is close to significance, more confident investors may be slightly more inclined toward high-risk investments, Indicating overconfidence over their abilities.

Crosstab

Expected Count

		Onascaleof1to5howconfidentareyouinyourabilitytom					
		1	2	3	4	5	Total
Howdoyoureacttomarketdownturnsorfinanciallosses	Adjust Investments to Minimize Losses	6.7	8.8	23.3	24.7	9.5	73.0
	Adjust Investments to Minimize Losses, Sell Off Investments to Avoid Further Losses	.6	.8	2.2	2.4	.9	7.0
	Sell Off Investments to Avoid Further Losses	2.6	3.4	8.9	9.5	3.7	28.0
	Stay Calm and Hold Investments	7.3	9.5	25.2	26.7	10.3	79.0
	Stay Calm and Hold Investments, Adjust Investments to Minimize Losses	1.2	1.6	4.1	4.4	1.7	13.0
	Stay Calm and Hold Investments, Adjust Investments to Minimize Losses, Sell Off Investments to Avoid Further Losses	.5	.6	1.6	1.7	.7	5.0
	Stay Calm and Hold Investments, Sell Off Investments to Avoid Further Losses	.2	.2	.6	.7	.3	2.0
Total		19.0	25.0	66.0	70.0	27.0	207.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	55.618[a]	24	<.001
Likelihood Ratio	50.948	24	.001
N of Valid Cases	207		

a. 23 cells (65.7%) have expected count less than 5. The minimum expected count is .18.

Figure 4.19:(Own Analysis)

Since the p-value is less than 0.05, there is a statistically significant relationship between confidence levels and how investors react to downturns. More confident investors are likely to hold or invest more during downturns (contrarian behavior). Less confident investors are more prone to panic selling or adjusting strategies.

5. Risk Aversion and Investment Preference

Crosstab

Expected Count

		UntestedvsBlueChip		
		Invest in a blue-chip company stock with moderate and stable returns	Invest in a new, untested startup with a high potential for returns (chance to double your money in a year, but also a c	Total
Whenmakinginvestmentdecisionshowmuchdoyouconsiderthep	1	8.9	3.1	12.0
	2	13.3	4.7	18.0
	3	31.0	11.0	42.0
	4	54.0	19.0	73.0
	5	45.8	16.2	62.0
Total		153.0	54.0	207.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	17.643[a]	4	.001
Likelihood Ratio	16.426	4	.002
Linear-by-Linear Association	14.338	1	<.001
N of Valid Cases	207		

a. 2 cells (20.0%) have expected count less than 5. The minimum expected count is 3.13.

Figure 4.20(Own Analysis)

- Pearson Chi-Square Value: 17.643
- Degrees of Freedom (df): 4
- Asymptotic Significance (p-value): 0.001

Interpretation:

Since the p-value (0.001) is less than 0.05, we reject the null hypothesis. This means there is a statistically significant relationship between how much people consider their investment decisions and their preference for blue-chip stocks vs. untested startups.

People who give more consideration to their investment decisions tend to prefer blue-chip stocks with stable returns. Those who are more risk-taking (and possibly consider investments less thoroughly) are more likely to invest in an untested startup with high potential returns but also a chance of losing everything.

6. Confirmation Bias

Crosstab

Expected Count

		Howoftendoyouignoreinformationthatcontradictsyourinitia					
		1	2	3	4	5	Total
Doyouseekoutinformationthatsupportsyourexistingbeliefs	no	6.4	10.4	13.8	5.5	2.8	39.0
	yes	27.6	44.6	59.2	23.5	12.2	167.0
Total		34.0	55.0	73.0	29.0	15.0	206.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	7.683[a]	4	.104
Likelihood Ratio	10.802	4	.029
N of Valid Cases	206		

a. 1 cells (10.0%) have expected count less than 5. The minimum expected count is 2.84.

Figure 4.21:(Own Analysis)

- Pearson Chi-Square Value: 7.683
- Degrees of Freedom (df): 4
- Asymptotic Significance (p-value): 0.104
- Likelihood Ratio: 10.802 (p = 0.029)

The Pearson Chi-Square test has a p-value of 0.104, which is greater than 0.05,

indicating that there is no statistically significant association between ignoring contradictory information and seeking information that supports existing beliefs.

However, the Likelihood Ratio (p = 0.029) is below 0.05, suggesting a possible weak relationship between the two variables.

A higher number of people who actively seek information that supports their existing beliefs also report ignoring contradictory information.

However, since the Chi-Square test is not significant, this pattern may not be strong enough to conclude a definitive relationship.

7. Herding Behaviour

Crosstab

Expected Count

		Haveyoueveravoidedchangingyourinvestmentstrategyevenwhe				
		Maybe	No	yes	Yes	Total
Haveyouevermadeaninvestmentdecisionbasedonthe recommend	Maybe	5.4	8.3	.2	18.1	32.0
	No	11.0	17.0	.3	36.7	65.0
	yes	.7	1.0	.0	2.3	4.0
	Yes	17.9	27.7	.5	59.9	106.0
Total		35.0	54.0	1.0	117.0	207.0

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	62.601[a]	9	<.001
Likelihood Ratio	21.485	9	.011
N of Valid Cases	207		

a. 7 cells (43.8%) have expected count less than 5. The minimum expected count is .02.

Figure 4.22:(Own Analysis)

- Pearson Chi-Square Value: 62.601
- Degrees of Freedom (df): 9
- Asymptotic Significance (p-value): < 0.001

- Likelihood Ratio: 21.485 (p = 0.011)
- Valid Cases: 207

The Pearson Chi-Square test has a p-value of < 0.001, which is highly significant. This indicates a strong association between making investment decisions based on friends or relatives and avoiding changes in investment strategy.

The Likelihood Ratio (p = 0.011) also confirms that this association is statistically significant.

A large proportion of those who have made investment decisions based on friends or relatives also tend to avoid changing their investment strategy, even when new information is available.

This suggests the presence of status quo bias or herd mentality, where individuals stick to their investment decisions because they trust the recommendations of their social circle.

CONCLUSION

This study explored the behavioral patterns that influence consumer decision-making in the context of personal investments, integrating concepts from consumer psychology, behavioral economics, and data analytics. The findings reveal that consumer choices are often driven not by objective evaluation of financial returns, but by **cognitive biases, emotional responses, and social influences**. These tendencies directly challenge traditional models of rational behavior and underscore the need for **behaviorally informed marketing and data-driven profiling strategies**.

Through detailed survey responses, it was confirmed that behavioral biases such as **overconfidence, familiarity bias, loss aversion, confirmation bias, framing effects**, and **herding behavior** play a critical role in shaping consumer preferences. Consumers frequently rely on perceived safety, social validation, or personal intuition when

evaluating options, often at the expense of rational analysis.

The analysis showed that **income levels significantly influenced consumer preferences**, with lower-income respondents more likely to favor stable, familiar options, while higher-income groups demonstrated a greater willingness to take risks. Interestingly, **age and gender did not yield significant statistical differences** in behavioral patterns, suggesting that cognitive biases cut across demographic lines.

Further, **high-confidence consumers** tended to express greater risk appetite and were more susceptible to overconfidence bias, while **low-confidence individuals** often leaned on peer influence or external advice, reflecting a tendency toward herding and indecisiveness. These insights are essential for marketers seeking to design communication strategies that resonate with target audiences and for analysts aiming to segment users based on decision-making behavior.

By leveraging these behavioral insights through analytics tools, marketers and product strategists can better understand how consumers interpret risk, trust, and opportunity. This research supports a more **personalized and psychologically attuned approach to marketing**, where data is not just used to predict transactions, but to understand the **underlying motivations and biases** that drive them.

5.1 Implications of the Study

For Marketers

- **Behavioral Segmentation**: The study supports the use of behavioral and psychographic variables—such as confidence level, risk perception, and susceptibility to peer influence—as **segmentation criteria**, in addition to traditional demographics. This allows for more precise targeting and campaign customization.

- **Framing and Messaging Strategy**: Understanding biases like **loss aversion** and **framing effects** enables marketers to present information in ways that align with consumer psychology. For example, messaging that emphasizes “avoiding losses” may be more effective for risk-averse consumers than promoting potential gains.

- **Influence of Social Proof**: The prevalence of **herding behavior** highlights the importance of using **social validation cues**—such as user reviews, testimonials, and popularity indicators—in marketing content to shape perception and drive adoption.

- **Personalized Product Positioning**: By recognizing decision patterns based on confidence and familiarity, marketers can craft differentiated product narratives. Stable, low-risk investment products can be marketed as secure and dependable, while high-return options can be framed to appeal to confident, aspirational segments.

For Analytics Professionals

- **Behavioral Data Integration**: The findings advocate for the integration of **behavioral variables into customer analytics models**, such as preference for familiar brands, emotional responses to risk, and decision-making style under uncertainty.

- **Predictive Modeling of Consumer Decisions**: Using survey data and statistical techniques like chi-square tests and correlation analysis, analysts can identify **predictive patterns** in consumer behavior, enabling data-driven recommendations and more accurate targeting strategies.

- **Consumer Profiling Based on Psychological Traits**: Instead of relying solely on observable behaviors, marketers and analysts can build **psychographic profiles** that classify consumers by behavioral tendencies—such as being data-driven, socially influenced, or emotionally reactive—enhancing product personalization and customer journey mapping.

- **Optimizing Campaign Effectiveness**: Behavioral insights can be incorporated into **A/B testing frameworks** to understand how consumers with different biases respond to variations in message tone, imagery, CTA framing, and offer types, thereby improving campaign efficiency.

For Financial Product Marketing and Strategy Teams

- **Behaviorally-Informed Product Design**: Financial service marketers can develop features and user interfaces that accommodate common biases, such as **default options for risk-averse users**, **educational prompts for overconfident users**, or **visual cues to counteract confirmation bias**.

- **Strategic Content Creation**: Creating educational content, explainer videos, and interactive tools tailored to different behavioral profiles can improve user trust, increase engagement, and support better decision-making at each stage of the customer journey.

For Policy and Education Stakeholders

- **Behavioral Literacy as a Core Skill**: Behavioral finance and decision science concepts should be integrated into **financial literacy programs**, equipping consumers with the self-awareness to identify their own biases and make more informed choices.

- **Transparent Communication Standards**: Regulators and institutions can promote communication practices that reduce **framing manipulation**, ensuring that product comparisons and disclosures are presented in ways that empower rather than mislead consumers.

For Investors

- Awareness of overconfidence bias can prevent excessive risk-taking, especially during market volatility.

- Understanding risk aversion can help investors balance their portfolios with an appropriate mix of safe and growth-oriented assets.

- Mitigating confirmation bias can encourage diversified research and open-minded decision-making.

- Recognizing herding behavior can encourage independent analysis rather than blindly following popular trends.

For Financial Advisors

- Advisors should assess behavioral biases when guiding clients, tailoring strategies that align with both risk tolerance and behavioral tendencies.

- Personalized risk profiling can help risk-averse clients feel comfortable with diversified investments while educating high-risk investors about potential downsides.

Policy and Financial Education Initiatives

- Financial literacy programs should emphasize common behavioral biases and their impact on decision-making.

- Regulatory bodies can promote transparent information presentation to reduce framing bias and encourage rational decision-making.

5.2 Final Reflection

Conducting this study on behavioral biases in consumer investment decisions has been an enriching and insightful academic experience. It provided an opportunity to go beyond theoretical concepts and engage with real-world consumer behavior using a structured, data-driven approach. The integration of marketing principles and analytics tools allowed for a multidimensional understanding of how individuals make financial decisions—not merely based on rational factors, but heavily influenced by emotions, cognitive shortcuts, and social dynamics.

From a **marketing perspective**, the project highlighted the critical role of **consumer psychology** in shaping perceptions of risk, trust, and value. It became evident that investment products, like any other consumer offerings, are evaluated through mental frames shaped by past experiences, emotional responses, and social validation. This understanding emphasized the need for behaviorally sensitive marketing strategies—ones that resonate with how

consumers think and feel rather than how they are assumed to act.

From an **analytics standpoint**, the project enhanced our skills in **quantitative research**, including survey design, statistical analysis, and pattern recognition across demographic segments. Tools such as chi-square testing and correlation analysis provided valuable insights into behavioral tendencies and helped establish meaningful relationships between psychological factors and decision outcomes. The process demonstrated how behavioral data can be translated into actionable marketing intelligence and used to inform strategic decision-making.

On a personal level, the project encouraged critical thinking, collaboration, and academic discipline. It also deepened awareness of the biases that affect not just consumers, but researchers and marketers themselves. Recognizing these human limitations is essential for designing ethical, empathetic, and effective marketing campaigns.

In conclusion, this research has reinforced the value of combining **marketing insight with analytical rigor**. It has provided a solid foundation for future work in consumer behavior analytics, behavioral segmentation, and customer-centric strategy development. The experience underscores the importance of approaching marketing not just as a creative discipline, but as one grounded in data, empathy, and psychological insight.

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ANNEXURES

Survey Questionnaire

Age *

a) 18-25

b) 26-35

c) 36-45

d) 45-60

e) 60 or above

Gender*

a) Male

b) Female

Profession*

a) Student

b) Salaried Employee

c) Housewife

d) Business Owner

e) Freelancer/Self Employed

f) Retired

Annual Income*

a) Less than 5 Lakhs

b) 5-10 lakhs

c) 10-15 lakhs

d) More than 15 lakhs

Q1) When faced with multiple investment options, on a scale of 1 to 5 how often do you feel capable of selecting the best one without hesitation?

Not capable

1

2

3

4

5

Capable

Q2) You have ₹10,000 to invest. Which option do you prefer?

a) Invest in a new, untested startup with a high potential for returns (chance to double your money in a year, but also a chance of losing all)

b) Invest in a blue-chip company stock with moderate and stable returns

Q3) When making investment decisions, how much do you consider the potential losses compared to potential gains?*

Not at all

1

2

3

4

5

Consider a lot

Q4) Have you ever made an investment based on the investment decisions of your friends or relatives?

a) Yes

b) No

c) Maybe

Q5) On a scale of 1 to 5, how influenced are you by market trends when making financial decisions??*

Not Influenced

1

2

3

4

5

Very Influenced

Q6) When investing ₹50,000, do you weigh the potential gains and losses equally?

a) Always

b) Often

c) Sometimes

d) Rarely

e) Never

Q7) Have you ever avoided changing your investment strategy even when presented with better options?

a) Yes

b) No

c) Maybe

Q8) How do you react to market downturns or financial losses?

a) Stay Calm and Hold Investments

b) Adjust Investments to Minimize Losses

c) Sell Off Investments to Avoid Further Losses

Q9) If you hear that a stock's price has increased by 20% recently, how likely are you to consider it a good investment without further analysis?

Not Iikely

1

2

3

4

5

Very Iikely

Q10) Do you seek out information that supports your existing beliefs when making financial decisions?

a) Yes
b) No

Q11) How often do you ignore information that contradicts your initial investment decision?

Never

1

2

3

4

5

Always

Q12) If given a choice between a fixed deposit (FD) offering 6% annual returns and a mutual fund with average returns of 12% but higher volatility, would you choose:

a) Fixed Deposit
b) Mutual Fund
c) No Preference

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