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Financial Portfolio Attribute Analysis Under Behavioral Constraints: A Data-Driven Optimization Framework

Thesis submitted
in Partial Fulfillment of the Requirement for the
Degree of

MASTER OF SCIENCE

IN

APPLIED MATHEMATICS

by

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Vidhi Vasudeva (24/MSCMAT/02)

Under the supervision of
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We, **Raghav Goel**, Roll No. 2K24/MSCMAT/01, and **Vidhi Vasudeva**, Roll No. 2K24/MSCMAT/02, hereby certify that the work which is being presented, entitled *"Financial Portfolio Attribute Analysis Under Behavioural Constraints: A Data-Driven Optimization Framework"*,in partial fulfilment of the requirements for the degree of Master of Science, submitted in the Department of Applied Mathematics, Delhi Technological University, is an authentic record of our own work carried out during the period from August 2025 to May 2026 under the supervision of Prof. L.N. Das.
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Abstract

This study combines behavioural finance and traditional models of portfolio performance to explore the effects of investors emotional , psychological and cognitive errors (like risk perception , anchoring bias , herd behaviour , overconfidence, loss aversion, and portfolio behaviour) and investors' financial characteristics (age, gender, income, and education) on the structure and performance of a portfolio. Unlike traditional finnacial and economics models that assume investors rational decision-making while making investment , investment behavior is fairly governed by psychological , emotional , cognitive errors. The research was quantitative in nature, and fundamental metrics were collected through a structured questionnaire framework from investors, and secondary data was used to calculate performance metrics such as return, risk, and the Sharpe ratio. The results show the negative influence of psychological and cognitive errors on the performance of a portfolio. The research found risk perception, anchoring bias, and portfolio behavior to be the main causes of risk-taking, lower returns, and poor investment decisions. Based on these results, a portfolio optimization model with behavioral bias adjustment was developed. The model improves the accuracy of portfolio performance by using psychological and financial attributes. provides a more realistic approach to an effective investor decision-making framework. The research shows that the incorporation of behavioral financial factors in traditional model theory can lead to more accurate, resilient, and real-world-applicable portfolio optimization and performance.

Keywords: behavioural finance, Portfolio Theory, Investor Psychology, overconfidence, Loss Aversion, herd behaviour

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Chapter 1

Introduction

Traditional financial theories such as Modern Portfolio Theory (MPT), the Capital Asset Pricing Model (CAPM), arbitrage theory, and the Fama-French three- and five-factor models have been used as a guide for an investor to make their investment decision. These emphasize the risk-return trade-off and provide frameworks for portfolio optimization. Moreover, these models make some assumptions that counteract the actual facts.

However, real-world scenarios often suggest that these assumptions deviate due to variations in investor preferences, financial constraints, and various other factors.

This makes it essential to study how investor financial and personal attributes influence portfolio characteristics such as return, risk, and diversification and help them in creating a portfolio personalized to them. This investigation attempts to integrate the concept of investors bias finance theories with traditional portfolio modeling to understand how individual investor attributes and biases affect their investment decisions and optimize the portfolio.

1.1 Traditional Portfolio Methods

Traditional portfolio models build the core structure of modern investor financial decision-making by providing a conceptual and systematic path in which the investor maximizes their return while minimizing risk. Such models have their own assumptions and limitations. Few of them are: -

1. Markowitz Modern Portfolio Theory (MPT) [5]
2. Capital Asset Pricing Model (CAPM) [6]
3. Arbitrage Pricing Theory (APT) [13]
4. Efficient Market Hypothesis (EMH) [17]
5. Fama-French Three-Factor Model [18]
6. Fama-French Five-Factor Model [14]

Model	Assumptions	Limitations	Future Scope
Markowitz (Modern) Portfolio Theory (MPT)	Rational and risk-averse Investors, normally distributed expected results, and markets are efficient	Unrealistic assumptions, highly sensitive to input data, ignores behavioral factors	Integration with behavioral finance: dynamic and multi-period models
Capital Asset Pricing Model (CAPM)	Efficient markets; rational investors, and returns depend on market risk (beta)	Oversimplified single-factor model; ignores anomalies; beta instability	Multi-factor extensions, behavioral CAPM, macroeconomic integration
Arbitrage Pricing Theory (APT)	Returns driven by multiple systematic factors, no arbitrage, linear relationship	Factors not clearly defined; complex estimation; less practical	machine learning for factor selection; dynamic factor models
Fama-French Three-Factor Model	size of market (SMB), and returns explained by valuable factors	Still incomplete: factor instability and data intensive	Extension to ESG and behavioral factors
Fama-French Five-Factor Model	Includes profitability and investment factors along with market, size, value	Possible overfitting; redundancy, and ignores momentum factor	Inclusion of momentum and liquidity; AI-based optimization

Table 1.1: Summary of Traditional Portfolio Models

1.2 Behavioral finance

Professional literature on financial theory and economics is primarily based on the assumption that investors are rational; they encompass all the available information in the portfolio performance decision-making process, and markets are assumed to be efficient. These assumptions are challenged by behavioral finance theory, and it examines how investors actually behave under psychological and emotional biases. It is an interdisciplinary research area in which emotions and cognitive errors are studied and how they alter the trading behavior of investors and their portfolio performance is investigated. Behavioral finance concepts are well elaborated in professional literature, and further to this, it is elucidated how behavioral finance affects investment decisions in [2].

Behavioral finance gives only an entry point to understand how individual emotional biases and cognitive errors may alter individual perceptions and investment making. Behavioral theory provides a vital explanation on why and how investors emotional and cognitive errors may alter individual viewpoints and portfolio performance decision-making. As a leading result, behavioral biases awareness may improve investment portfolios' performances and explain anomalies in investment portfolio performance. Behavioral finance also provides observations into market anomalies [2].

However, CFA Institute's study (2023) [2] suggests that combining behavioral traditions might give prominent results.

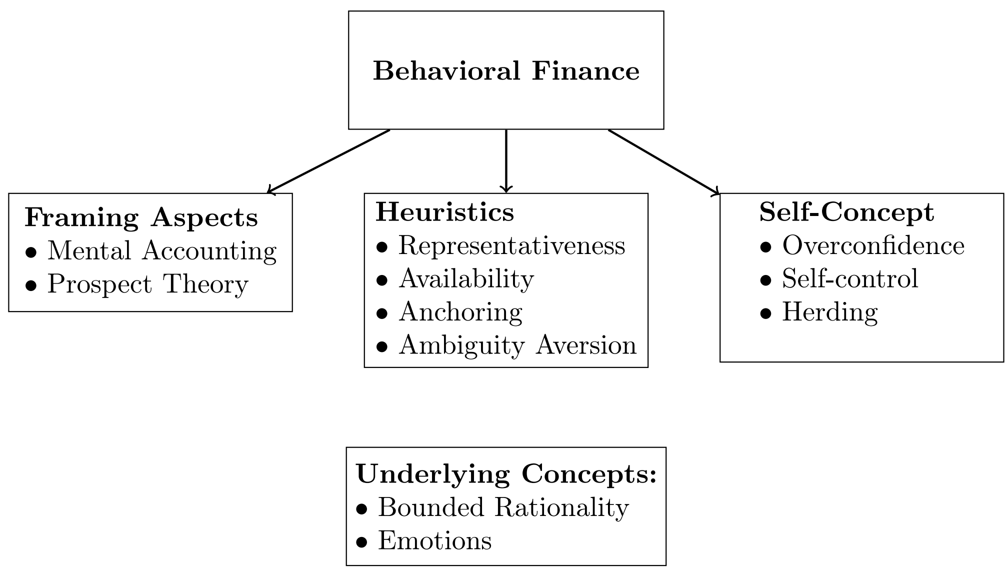

Figure 1.1: Classification of behavioral finance
Source: Adapted from [2]

In addition to the above biases/anomalies, sharp fixing of asset prices, patterns like momentum, and the clustering effect also disturb the underpinning assumptions of traditional models and, therefore, add to the urgency to learn more about the investor behavioral attributes and biases [15].

In this study the behavioral finance attributes used relate to cognitive biases such as

1. Portfolio Behavior
2. Risk Perception
3. Anchoring Bias
4. overconfidence
5. loss aversion
6. herding behavior

1.2.1 Portfolio Behavior

The portfolio behavior is also significantly affected by behavioral biases. They influence the way investors construct and manage their investments. Loss aversion and anchoring are just two examples of many biases that lead investors to prematurely sell and retain (the disposition effect). Investors invest in their homebound assets as they feel more comfortable due to home country bias; however, this will lower the diversification of the portfolio and thus increase risk. Mental accounting makes a person think of investments as different items: he does not manage the whole portfolio. Overconfidence results in overtrading, which will lower the overall portfolio return since higher transaction costs and poor decision-making would arise.

1.2.2 Risk Perception

Risk perception is how an individual investor views financial risk, which can differ significantly from market risk. Perception is impacted by psychological biases such as probability weighting and availability heuristics; past experiences and emotions all contribute to this. Hence, investors tend to take too much risk in rising markets because of overconfidence and too little after markets decline because of excessive fear.

1.2.3 Anchoring Bias

Anchoring bias is where an investor relies solely on the primary source information they learn when making decisions. It could be the price at which a stock was bought or the price at which it was historically available. Even if that piece of information is no longer relevant, investors still use it as a reference point on which to base all future up- or down-decisions on individual securities. If this results in having to realize a loss and sell something for less than what an investor paid for it, it is difficult for an investor to go below their original cost when selling assets, for example.

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1.2.4 Overconfidence

The overconfidence bias generates overconfidence in the investor's knowledge and the accuracy of their prediction. The bias in which investors put too much trust in their own intuitive reasoning, judgment, and/or psychological abilities. This happens because investors may overestimate their own knowledge levels, access to different sources of information, and abilities. As it is very hard for the self-perception of individuals of their knowledge and abilities to change, this bias is very difficult to correct. This concept has been delivered from a large number of psychological tests and surveys where respondents do two things: overestimate their own prediction capabilities and the accuracy results caused by the bias itself [2].

1.2.5 Loss aversion

It is the core concept of prospect theory. It explains the determination of an investor to go an extra mile to avoid any investment losses instead of just gaining returns. It is incorporated in several financial and economic literature pieces, and it suggests that from a cognitive perspective, losses are far greater than gains. Loss aversion is a tendency to hang onto losses even when the investment will never again go up in profitability. It encourages people to avoid risk when they think about potential gains [2].

1.2.6 Herding behavior

The behavior shown by the investors when they disregarded their own knowledge, analysis, or rational decision and started following the actions of a larger population. "They're herd followers; they don't make independent decisions based on data. They just follow the market trend, the popular sentiment, or what the institutions are doing. This effect is particularly strong during times of market uncertainty, when people use collective behavior as a proxy for superior information. In behavioral finance, herd behavior is a violation of rationality because it is the substitution of analytical thinking with social conformity.

1.2.7 Overview

Behavioral finance is an important field to study and improve investor decision-making, as it narrows the bridge between traditional financial theories and practical world market behavior. The traditional paradigm assumes rational investors and efficient markets, whereas literature on behavioral finance and economics acknowledges that decisions are often driven by cognitive and emotional errors, biases, and social factors. Behavioral finance is a more realistic model to explain deviations from optimal investment strategies in this context, especially for the analysis of attributes such as risk perception, portfolio behavior, anchoring bias, overconfidence, loss aversion, and herding.

Its importance stems from its ability to identify systematic patterns of irrationality that are directly relevant to portfolio choice, risk assessment, and asset pricing. Introducing behavioral considerations into financial modeling has proved to be useful for researchers and practitioners alike in understanding anomalies such as over-trading, under-diversification, misjudging risks, overvaluing expected gains, and failing to maintain portfolio diversification. Moreover, behavioral finance improves the performance of statistical and optimization techniques by pointing out where and why purely quantitative models may fail if human behavior is disregarded.

In practice, integrating behavioral finance with computational tools such as regression analysis, correlation examination, and portfolio model optimization using Microsoft Excel allows the development of investment decision-making frameworks that are data-driven and investor behavior-aware. More refined and better risk management and more disciplined investment techniques resulted from this. Ultimately, behavioral finance is valuable, not only as a theoretical extension but also as a required component in the development of advanced financial models that are more in line with the actual behavior of investors and increased portfolio performance.

1.3 Prospect Theory

Prospect theory (Kahneman and Tversky, 1979) is a breakthrough in the study of investor decision-making under uncertainty and risk. Classical theory assumes that decision-making is rational. Prospect theory, by contrast, recognizes that investors assess results relative to a reference point (generally a commodity price of purchase or perceived breakeven level) rather than in absolute wealth terms. It has direct implications for investment behavior, in that the psychological weight placed on potential losses is about twice the weight placed on equivalent gains. This phenomenon is at the heart of loss aversion. This thesis studies prospect theory as a theoretical framework to understand and connect the investors' cognitive factors such as risk perception, portfolio behavior, anchoring bias, overconfidence, loss aversion, and herding. The investor under prospect theory is not a rational utility maximizer. Rather, investors' behavior is systematically biased by the way in which choices are framed, the mental accounting of gains and losses, and the impact of past regret on future behavior.

1.3.1 Regret Aversion

When investors avoid or run away from the pain of regret from making bad investment choices. According to buyers of stocks, it's not a good idea to sell stocks that aren't doing well because you might lose money, and then stocks are taxed less by showing that the investments have lost money.

1.3.2 Framing

In behavioral finance, a few terms that are primarily used in specific situations and issues refer to framing. There are a lot of investment options, but the likelihood is that an investor will pick the one who speaks or listens most of the time.

1.3.3 Self-Control

People who make decisions always want to avoid losing money, so they look for safe places to spend. Self-control keeps getting better for investors so they can make investments. To keep investors from spending too much, they should keep putting money into business expenditure pools.

People are different in their behavior and act accordingly in their own decision-making process. So an individual, according to his own observation and ability, lands on a particular reaction against market anomalies. Computational structures of different strategies are devised by the investors based on their self-awareness and experience. Further refinements are done to these investment strategies by psychological bias identification through The criteria for investment fluctuate, thus influencing the critical thinking in making investment decisions. Investment environments of diversifying and scheming also contribute vitally to an individual's investment decision-making strategies. Psychology relates risk and return to feelings and emotion, further assisting in decision-making about optimal investment perspective [8].

1.4 Computational tools and Optimization techniques

1.4.1 Computational tools

"Computational tools" refer to a broad set of quantitative and statistical techniques used to structure investor investment data and support their investment decision-making in a systematic and objective manner. These tools include methods such as regression analysis, correlation analysis, descriptive statistics, and optimization techniques. In finance, computational tools formulate collective market data to provide meaningful insights.

Computational tools serve as a bridge between these two perspectives by:

1. Quantifying behavioral biases rather than treating them as abstract concepts
2. Embedding behavioral tendencies into traditional mathematical models and empirical analysis
3. Allowing deviations from rationality to be measured, tested, and corrected
4. Providing data-driven constraints that reduce subjective decision-making

Regression Analysis in Bridging the Gap

Regression analysis plays a significant role in connecting the divisive gap between behavioral factors and modern portfolio theory by linking behavioral patterns with financial outcomes by forming cause-and-effect relationships.

1. Identifies how behavioral factors influence returns and risk.
2. Testing statistical significance (P-values, R^2), it reduces reliance on intuition and subjective beliefs.
3. Models can incorporate behavioral variables alongside traditional financial factors, creating hybrid models.
4. Regression analysis converts behavioral biases into quantifiable variables, making them compatible with MPT-based decision frameworks.

Correlation Coefficient in Bridging the Gap

Correlation analysis helps in understanding relationships between assets, which is central to portfolio diversification in MPT.

1. It improves diversification by encouraging selection of low or negatively correlated assets.
2. It provides an objective measure of co-movement, reducing emotional or trend-based decisions.
3. It helps investors recognize hidden risks arising from behavior-driven clustering of assets.

Descriptive Statistics in Bridging the Gap

Descriptive statistics provide a foundational understanding of data, which is critical for both behavioral and traditional finance.

1. Mean (Average Return) : Offers a realistic expectation of returns and Reduces overconfidence by grounding expectations in historical data

2. Median: Provides a robust central tendency unaffected by extreme values; moreover, it Helps counter distorted perceptions caused by market anomalies

3. Mode: The most frequently occurring outcomes; moreover, it Useful in recognizing repetitive behavioral patterns in trading

4. Variance (Risk Measure) : Quantifies dispersion and uncertainty and Helps loss-averse investors understand and manage risk objectively

1.4.2 Optimization Techniques

Optimization refers to the mathematical procedures that can be used to maximize or minimize the objective function subject to multiple restrictions to provide the best possible optimal solution. As most traditional models remain almost theoretical, they assume investor behavior remains completely rational while investing and consider any behavioral bias without converting it into optimizable variables. Optimization techniques such as Microsoft Excel are used to construct an efficient and optimal portfolio performance model that finds out the optimal adjusted weights allocated to each asset in the portfolio to minimize risk and maximize return to overall increase the performance of investors' portfolios. Microsoft Excel is used, as it provides an easy and efficient implementation of such a model through formulas, matrix calculation and Microsoft Solver by adjusting allocation of weights to asset according to the objective function and constraints to have an optimal investor portfolio.

Asset Selection For Portfolio Construction

Assets are financial instruments for an investor portfolio construction.Different assets according to Indian general standards, along with their expected return and std dev. (risk), are taken under consideration for overall reducing portfolio risk and diversifying the investor portfolio.

Table 1.2: Expected Annual Return and Risk of Selected Assets

Asset	Expected Annual Return	Std Dev (Risk)
Large-cap equity (Nifty 50)	12%	18%
Mid-cap equity	15%	24%
Government bonds	7%	5%
Gold	10%	16%
Real estate (REITs)	9%	12%
Cash / FD	6%	1%

Covariance Matrix Analysis of Asset Returns

Covariance matrix measures the relationship between returns of different assets in the portfolio. This helps to see whether returns on asset move in the same or opposite direction. This matrix is important for calculating the risk of a portfolio and building an optimized portfolio.

Covariance Formula:

$$\text{Cov}(L, A) = \frac{\sum_{Z=1}^{Y}(L_i - \bar{L})(A_Z - \bar{A})}{Y - 1}$$

Where:

- L_i, A_i = Individual insights of parameters L and A
- $\bar{L}, \bar{A}$ = Mean metrics of L and A
- Y = Number of insights

  The covariance measure plays a vital role in evaluating portfolio risk and diversification benefits. The covariance-based portfolio optimization framework was originally introduced in the Modern Portfolio Theory developed by Markowitz [5].

Development of the Behavioral Distortion Matrix

The distortion matrix, is a way to introduce behavioral finance factors into the risk structure of that model. We show how to modify the original risk structure such that it represents more realistic investor behavior and leads to portfolios that depend on both financial and psychological properties of investment decision-making.

Portfolio Optimization Metrics

1. Portfolio return -Portfolio Return Portfolio return is the overall or total expected return from all selected assets of the portfolio. It's the weighted mean of individual asset returns founded on their allocation weights. In optimization, portfolio return used as one of the key objectives.

2. Variance - Variance shows how much the individual values in a data set differ from the mean, which helps to understand and calculate the risk. The notion of variance is applied in portfolio optimization to lower the level of risk and create more stable investment portfolios.

3. Standard Deviation - Standard deviation variance is actually standard deviation squared. When it comes to business, you'll primarily use this statistic to get a sense of how volatile portfolio returns are-the lower the standard deviation, the more consistent returns tend to be, and therefore the lower the risk associated with making an investment.

4. Sharpe Ratio -Sharpe Ratio computes the performance of a portfolio by evaluating its returns in relation to the risks taken by investors. This ratio basically shows how much additional return an investor earns for each token of risk taken on. A higher Sharpe ratio indicates more optimal and efficient portfolio because it provides prominent returns for the amount of risk taken. The computation of the Sharpe Ratio follows the methodology proposed by Sharpe , William F. [6].

   Sharpe Ratio Formula

$$l = \frac{R_y - R_z}{\sigma_a}$$

here:

- l = Sharpe Ratio
- R_y = Portfolio Return
- R_z = Risk-Free Rate
- σ_a = Portfolio Std Dev.

Constraint Structure

The traditional portfolio model is optimized by using a set of constraints that reflect practical investment requirements:

1. Constraint of non-negativity: Asset under consideration must be higher or equivalent to zero, reflecting the constraint applicable to typical Indian retail investors who do not engage in short positions
2. Upper bound constraints: Each asset weight less than 100% of the total amount, reflecting no individual asset dominates the portfolio through a leverage position
3. Full Investment Constraint: The sum of all weights should be 100%, reflecting that overall money invested is fully deployed to all 6 assets under consideration at all times. A minor numerical tolerance does not materially affect the economic interpretation of the end results

Portfolio Optimization using Excel Solver

Excel Solver is used in this study to determine the best optimal investor portfolio, as it automatically adjusts weights allocated to each asset under portfolio construction based on the given objective function and constraints. Solver helps in maximizing the Sharpe ratio and modeling an effective and optimal investor portfolio.

1.5 Problem Formulation and Objectives

Traditional theories such as the efficient market hypothesis do not encompass the behavioral elements influencing an investor at this current period in time as assessed by behavioral finance. Thus, the following research questions are The present thesis determines to fill this divisive gap with regard to the effects of cognitive and affective aspects on investors. The solutions to these research issues are important to create general understanding about the market anomalies. Therefore, the study is an effort to fill the gap in the altercations between and among the investors cognitive and psychological errors to study their relationship. The results of the empirical study would be helpful in exposing the methodologies that help in avoiding the adverse impacts of such errors on the investor portfolio performance and in demanding more rationality when making decisions regarding investing. This thesis has provided opinions on the stability and improvement of the investors' portfolio-making performances and decisions [2]

Objectives of this Work

The primary goals of this thesis are the following:

1. Analyzing the effect of various behavioral biases affecting a person's financial decision-making.
2. Comparing the traditional outputs with behaviorally corrected outputs.
3. Trying to optimize traditional portfolio modeling by incorporating behavioral bias constraints.

Chapter 2

Literature review

Traditional financial models generally assume that investors behave rationally. These assumptions have long served as the basis for portfolio optimization and increasing performance. However, growing empirical research shows that an investor's core tendency is often altered by various cognitive errors and emotional and psychological biases, leading to consistent deviations from rational investment decision-making thinking, resulting in behavioral finance emerging as a complement to traditional theory. By integrating psychological insights, it provides a stronger ground for statistically analyzing portfolio performance with different investors' attributes and optimizing investor financial portfolios.

2.1 Brief Overview

1. P.K. Parida and S.K. Sahoo (2015) highlight the relevance of Markowitz's mean-variance optimization in balancing the expected investment return and risk via convex quadratic programming. This points to the inadequacy of traditional probabilistic models to represent real-world market uncertainty and investor behavior. The study shows that classical models would require more flexible and realistic computational frameworks since they struggle to include behavioral factors [4].

2. Majid Zanjirdar (2020) contrasted conventional portfolio optimization models such as mean-variance, VaR, and CVaR with contemporary advanced metaheuristic algorithms, namely Genetic Algorithms (GAs) and the Krill Herd Algorithm. Results revealed the inherent structural constraints in classical models regarding real-world portfolio constraints; on the other hand, the metaheuristic and fuzzy approaches need to adequately address a complicated problem, which is a multi-objective optimization problem type. The fact also carries an implication that there is a missing gap that still remains, which is developing a generalized hybrid optimizer to handle market uncertainty systematically based on a sound statistical foundation [3].

3. S.S. Agrawal, K.P. Sahai, and J. Venu Gopal (2024) focused on the involvement of psychological and behavioral errors in financier behavior while carrying out investment decisions. The authors' analysis of these psychological pitfalls under behavioral finance reveals that deeply rooted biases have a tendency to shroud logical thought, and hence, a set of regular irrational investment

decisions is being made. One caveat raised by their article is that it fails to consider the ways in which new technological tools may hinder, disturb, distort, or otherwise impede a rational investor financial and precautionary decision-making process when it comes to market selections [1].

4. Neharika Sobti (2016) uses Fama-MacBeth two-pass regression to compare CAPM and the Fama-French three-factor model. The results showed that the Fama-French model performed better than the CAPM and that a notable size effect was accompanied by a weak value effect. The study identified a non-linear association between beta and excess returns, thereby questioning the assumptions of the traditional CAPM, and found that the size anomalies are persistent and indicative of market inefficiencies. The author suggests how to incorporate behavioral deviations so as to obtain a deeper understanding of market realities [7].

5. Muhammad Atif Sattar, Muhammad Toseef, and Muhammad Fahad Sattar (2020) examined the alterations of investors' cognitive factors on their portfolio choices and performance, using computational and statistical methods such as regression methodology. The study found that behavioral, emotional, and cognitive errors such as risk perception, loss aversion, and portfolio behavior have a larger influence on investor behavior than prospect-related factors. The authors did not know about the interaction of these biases and their embedding in different cultural portfolio contexts [8].

6. Yuyang Wang (2023) stated that behavioral, psychological, and emotional factors could affect investors' critical thinking while making investment decisions. In fact, those behaviors were irrational because an overly optimistic self-assessment and misjudgment of risks prevailed. The lack of appropriate strategies and methods to apply collectively among various types of investors was also one aspect concerning the research gaps [9].

7. Dr. Vinay Kumar and Khalid Mehraj (2024) conducted a detailed study on 398 investors in Jammu and Kashmir to analyze the influence of investors' cognitive factors on their critical thinking while making portfolio performance decisions. Hence, to assess the altercations of cognitive and emotional errors of the investors on their critical thinking while making investment decisions. The study finds that biases like loss aversion, overconfidence, herd behavior, etc. have a significant influence on investor behavior, which results in irrational financial decisions [10].

The following table from S.S. Agrawal, K.P. Sahai, and J. Venu Gopal (2024) summarizes important research on traditional finance theories, behavioral finance, and the combination of both in explaining investor behavior [1].. It presents its major findings, methodological strategies, and research voids and forms a key basis for the current work.

Table 2.1: Studies Integrating Traditional Finance and Behavioral Finance

Year	Author(s)	Findings	Research Gap
2006	Daniel, Hirshleifer, & Subrahmanyam	Overconfidence leads to overreaction.	Need for deeper analysis across different market sectors.
2004	Lo et al.	The efficient market hypothesis is challenged by momentum effects by showing stock performance continuation.	Further study is required across varying market cycles.
2012	Ben-David & Hirshleifer	Loss aversion causes market underreaction and overreaction, creating momentum and reversals.	Limited understanding across investor categories and market conditions.
2017	De Bondt & Thaler	Stock prices overreact to information, resulting in price reversals and mean reversion.	Need to examine impacts across different asset classes.
2018	Shefrin et al.	Behavioral finance explains irrational investor behavior and market anomalies beyond traditional models.	Need to evaluate behavioral impacts on emerging financial technologies.
2014	Jegadeesh & Titman	Cognitive biases contribute to persistent market mispricing and trading opportunities.	Further research is needed across different market environments.
2018	Nofsinger	Behavioral bias must be integrated into traditional portfolio theories for better portfolio performances.	Limited innovation of technologies for hybrid behavioral-financial models.
2019	Ma et al.	Cognitive biases contribute to momentum and reversal anomalies in financial markets.	Need for frameworks to reduce behavioral bias in investment decisions.

Source: Adapted from [1]

These studies conclude that mitigation of the behavioral finance factors is important to improve investor investment decision-making under various market uncertainties. It is advised for investors to

- adopt to diversified sources for information
- objective self-assessment
- reviews from a professional portfolio to decrease the effect of behavioral factors.
- utilizing planned decision-making structures
- getting professional advisory
- artificial intelligence for better investment results.

2.1.1 Major points of Research Gaps

1. Most of the analysis was theoretical and psychology-based.
2. No optimization framework including the behavioral attributes of a person.

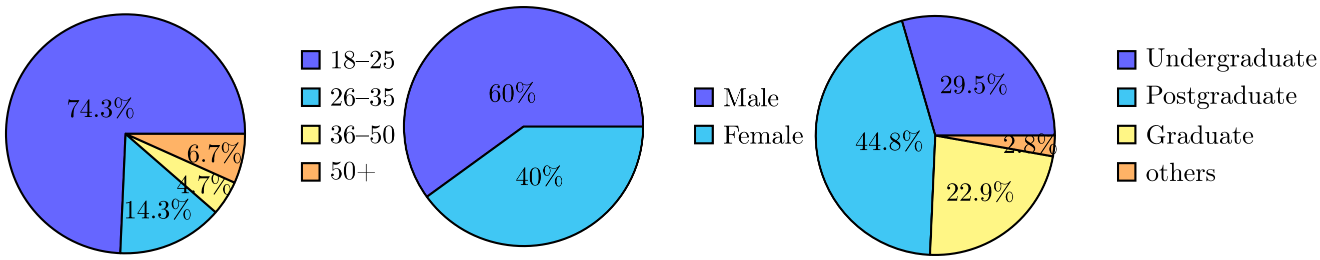
Chapter 3

Methodologies

The present study is aligned with fundamental research as the gaugeable approach with the initiative of explaining any alteration reflected in their portfolio performances by investors cognitive and emotional errors. Standardized questionnaires have been used for the collection of primary data from a random sample of 105 individual investors belonging to different age groups. The survey instrument of this investigation will probe the alteration impact delivered by the selected core cognitive biases (risk perception, portfolio behavior, anchoring bias, overconfidence, loss aversion, and herding). This set of Likert-scale questions is used to assess the number of such biases of the respondents. Moreover, to obtain information on the respondents' gender, age, education, and investment experience for adjusting variability, demographic questions were asked. An online survey was constructed in order to reach as many individual investors as possible relating to different cultures and backgrounds. The application of statistical and computational techniques such as regression and correlation analysis with descriptive statistics for data analysis and also to create an efficient portfolio optimization model for the improvement of portfolio performance is performed under this empirical study. Descriptive statistics provide the tale of the demographic features and the distribution of the responses in question. The assumptions about the vital alteration of investor cognitive and emotional errors in their investing decisions are investigated with the multiple regression analysis in Python programming as for the approaches to testing the hypotheses. Overconfidence, loss aversion, herding, risk perception, portfolio behavior, and anchoring bias might be independent variables. The interrelationship between the different cognitive biases was evaluated by Pearson's correlation coefficients, and ANOVA was deployed to investigate the diversity among demographic groups with respect to cognitive biases. These techniques offer a systematic and objective way to explore relationships between variables and test research ideas. for finding the weightage and direction of correlation among variable correaltion analsysis in computed. Python allows quick data processing, visualization, and reproducibility of results. These methodologies work together to add to the credibility and robustness of the findings and present empirical proof of alteration of investor emotional and cognitive errors in their portfolio performance and investment decision-making behavior [1].

3.1 Questionnaire Data Visualization

3.1.1 Demographic Analysis



(a) Age Distribution (b) Gender Distribution (c) Education Level

Figure 3.1: Demographic Profile of Respondents

3.1.2 Behavioral Bias Analysis

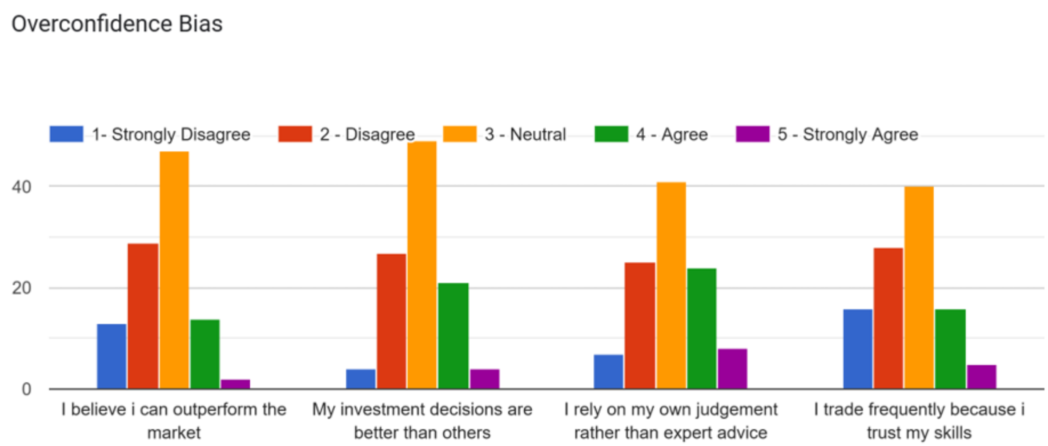


Figure 3.2: Overconfidence Bias Among Investors

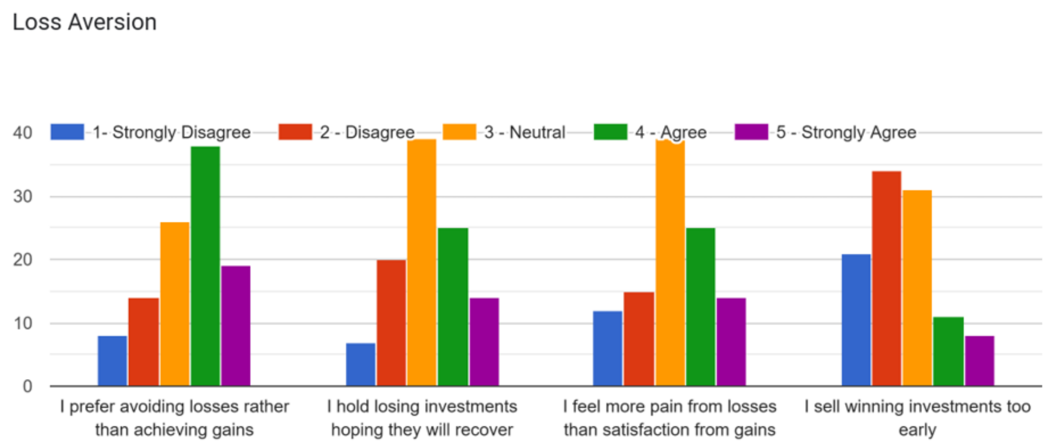


Figure 3.3: Loss Aversion Behavior Among Investors

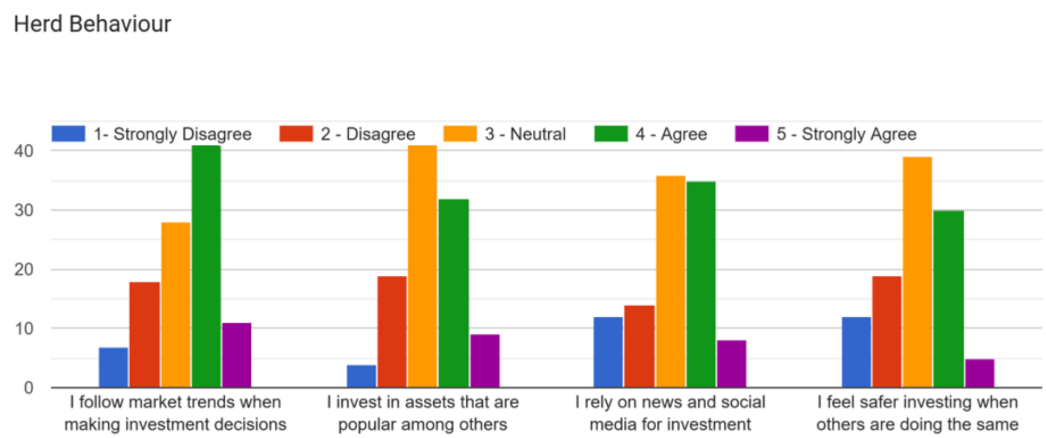


Figure 3.4: Herding Behavior Among Investors

Table 3.1: Summary of Survey Responses

Question	**Category**	**Percentage**
Monthly revenue	less than Rs 20k	44.8%
	Rs 20k – Rs 50k	18.1%
	Rs 50k – Rs 100k	15.2%
	more than Rs 100k	21.9%
Investment Experience	Below 1 year	55.2%
	1–3 years	28.6%
	3–5 years	4.8%
	Above 5 years	11.4%

Question	Category	Percentage
Investor Type	Beginner	68.6%
	Moderate	22.9%
	Experienced	8.6%
Assets Invested	Stocks	57.1%
	Mutual Funds	61.0%
	Crypto	11.4%
	Bonds	11.4%
	Others	26.7%
Investment Frequency	Regularly	35.2%
	Occasionally	35.2%
	Rarely	29.5%
Investment Goal	Wealth Creation	61.9%
	Short-term Gains	17.1%
	Retirement	4.8%
	Safety	16.2%

Statement	SD	D	N	A	SA
Willing to take higher risks	Low	Medium	High	Medium	Low
Prefer safe investments	Low	Medium	Medium	High	Medium
Market swings shape decisions	Low	Medium	High	Low	Low
Panic during downturns	Low	High	High	Medium	Low
Confident during rising markets	Low	Low	Medium	High	Medium

3.2 Descriptive Analysis

For the assessment and presentation of the population-based traits ,Descriptive statistics are computed. The central tendency, such as mean, standard deviation, minimum, and maximum values, was computed, and metrics variability was assessed. This evaluation resulted in the identification of the overall investor's behavioral tendencies in the context of:

1. anchoring bias
2. risk perception
3. portfolio behavior
4. loss aversion
5. overconfidence

6. herd behavior

Bar charts and pie charts were utilized as graphical tools for visual representation of demographic distributions and scores of behavioral variables.

Table 3.2: Descriptive Statistics of Behavioral Factors

Factor	Q	Mean	Median	Mode	Variance	Std Dev.	Min	Max
Loss Aversion	Q1	3.4381	4.0000	4	1.3447	1.1596	1	5
	Q2	3.1810	3.0000	3	1.2073	1.0988	1	5
	Q3	3.1333	3.0000	3	1.3667	1.1690	1	5
	Q4	2.5333	2.0000	2	1.3282	1.1525	1	5
Overconfidence Bias	Q1	2.6476	3.0000	3	0.8650	0.9301	1	5
	Q2	2.9429	3.0000	3	0.7659	0.8752	1	5
	Q3	3.0095	3.0000	3	1.0480	1.0237	1	5
	Q4	2.6762	3.0000	3	1.1249	1.0606	1	5
Herd Behavior	Q1	3.2952	3.0000	4	1.1716	1.0824	1	5
	Q2	3.2190	3.0000	3	0.9419	0.9705	1	5
	Q3	3.1238	3.0000	3	1.2249	1.1068	1	5
	Q4	2.9714	3.0000	3	1.1242	1.0603	1	5
Anchoring Bias	Q1	3.3524	3.0000	4	0.9227	0.9606	1	5
	Q2	2.7619	3.0000	3	0.8370	0.9149	1	5
	Q3	3.7048	4.0000	4	0.8832	0.9398	1	5
Risk Perception	Q1	3.1810	3.0000	3	1.1881	1.0900	1	5
	Q2	3.5333	4.0000	4	1.2128	1.1013	1	5
	Q3	3.4571	4.0000	4	0.9813	0.9906	1	5
	Q4	2.7714	3.0000	3	1.0434	1.0215	1	5
	Q5	3.6095	4.0000	4	0.6634	0.8145	1	5
Portfolio Behavior	Q1	3.6286	4.0000	4	1.1588	1.0765	1	5
	Q2	3.6095	4.0000	4	1.0095	1.0048	1	5
	Q3	3.2190	3.0000	3	1.0573	1.0283	1	5
	Q4	2.6857	3.0000	3	1.1791	1.0859	1	5
	Q5	2.8438	3.0000	3	1.2911	1.1363	1	5

Table 3.3: Combined Statistics of Behavioral Biases

Behavioral Bias	**Mean**	**Median**	**Mode**	**Variance**	**Std Dev**	**Min**	**Max**
Loss Aversion	3.0714	3.0000	3	1.4125	1.1885	1	5
Overconfidence Bias	2.8190	3.0000	3	0.9696	0.9847	1	5
Herd Behavior	3.1524	3.0000	3	1.1223	1.0594	1	5
Anchoring Bias	3.2730	3.0000	4	1.0271	1.0135	1	5
Risk Perception	3.3105	3.0000	3	1.1038	1.0506	1	5
Portfolio Behavior	3.2035	3.0000	3	1.2770	1.1300	1	5

[2] The table presents the combined descriptive statistics for behavioral biases. Risk perception shows the highest mean, indicating relatively stronger influence among investors, while overconfidence exhibits the lowest mean, suggesting weaker presence. Loss aversion demonstrates the highest variance, indicating greater variability in investor responses.

3.3 Normality Analysis

3.3.1 Normality Analysis

To break down the normal distribution of behavioral variables included in the study, normality analysis was performed. Assessment of normalcy is an important prerequisite before the application of parametric analytic measures such as correlation analysis, ANOVA, and multiple regression analysis. In the present study, the normalcy of variables was checked by:

- Shapiro-Wilk Test,
- Skewness,
- and kurtosis measures.

The Shapiro–Wilk test was the major statistical test used to test for normality. The test hypotheses were the following:

Null Hypothesis (H_0)

$$H_0 : \text{The data is normally distributed}$$

Alternative Hypothesis (H_1)

$$H_1 : \text{Data follows a normal distribution}$$

The decision rule for the Shapiro-Wilk test was the following:

- If the p-value is less than 0.05, then the data is not normally distributed.
  $P < 0.05$: Data is not strictly normal

In addition to the Shapiro–Wilk test, skewness and kurtosis values were generated to examine the form and distribution features of the data.

- Skewness gauges symmetry of the distribution.
- Kurtosis gauges the peakedness or flatness of the distribution.

The permissible range for both skewness and kurtosis was taken as ± 2, which is indicative of approaching normality in behavioral and social scientific research. The investigation has been conducted on the sample size of 105 respondents. While testing for normality, the Central Limit Theorem was also addressed. Therefore, modest departures from perfect normalcy were tolerated for the sake of subsequent parametric statistical analysis. Later, the results of normality analysis were utilized to justify the use of correlation analysis, ANOVA, and regression analysis in the study. The test was done using the Python programming language and libraries like Pandas, NumPy, SciPy, Statsmodels, Matplotlib, and Seaborn.

Table 3.4: Normality Test Results

Variable	Shapiro-Wilk p-value	Skewness	Kurtosis	Interpretation
Loss Aversion (LA)	0.043	0.162	0.327	Approximately Normal
Overconfidence (OC)	0.004	0.482	0.768	Approximately Normal
Herd Behavior (HB)	0.054	-0.300	0.192	Normal
Anchoring Bias (AN)	0.037	-0.250	0.499	Approximately Normal
Risk Perception (RP)	0.000	-0.700	3.354	Slight Deviation
Portfolio Behavior (PB)	0.003	0.110	1.115	Approximately Normal

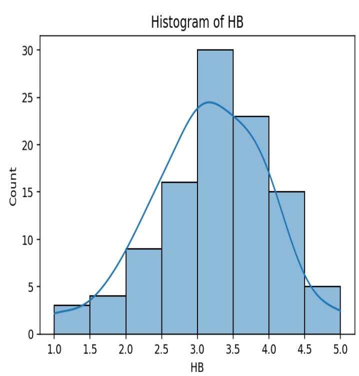


Figure 3.5: Herd Behavior Among Investors

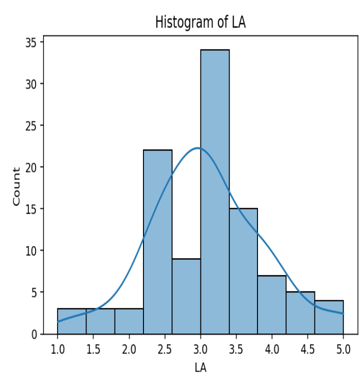


Figure 3.6: Loss Aversion Behavior Among Investors

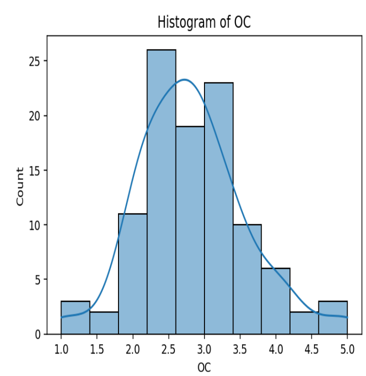


Figure 3.7: Overconfidence Behavior Among Investors

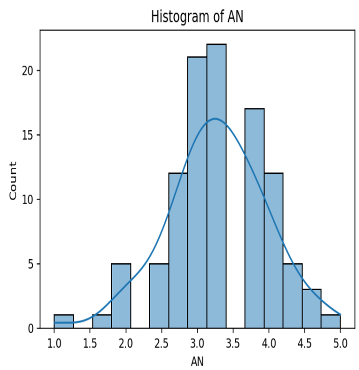


Figure 3.8: Anchoring Bias Among Investors

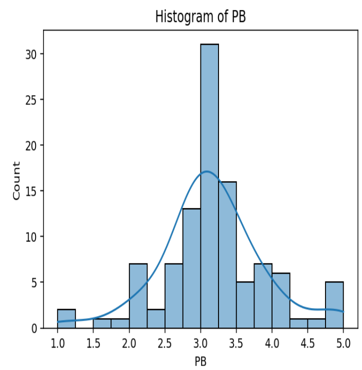


Figure 3.9: Portfolio Behavior Among Investors

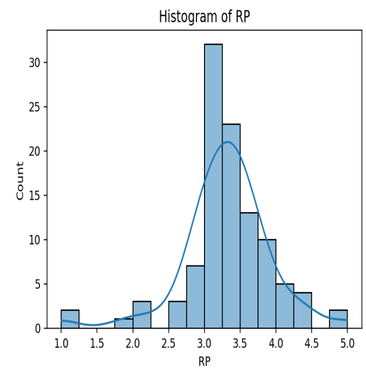


Figure 3.10: Risk Perception Among Investors

3.4 Correlation Analysis

To evaluate the link between behavioral biases and portfolio behavior of investors, an empirical study on correlation was assessed. It is a measure of how much two parameters tend to move together. When the two parameters tend to move in the same direction, it is known as a positive correlation. The counter of it is known as the negative correlation.

to determine for the assessment of the strength and direction of correlations between the parameters The Pearson correlation coefficient was computed. Pearson correlation analysis was chosen since the present study utilized continuous numerical variables from Likert scale responses, and the method is commonly utilized in behavioral finance studies to analyze linear correlations between psychological and financial factors. The Pearson correlation coefficient is determined by the formula:

$$l = \frac{i\sum CT - (\sum C)(\sum T)}{\sqrt{[i\sum C^2 - (\sum C)^2]\,[i\sum T^2 - (\sum T)^2]}}$$

here:

- l = Pearson correlation coefficient
- C = values of parameter C
- T = values of parameter T
- i = number of insights
- $\sum CT$ = sum product of paired insights
- $\sum C$ = sum of values of parameter C
- $\sum T$ = sum of values of parameter T
- $\sum C^2$ = squared sum values of C
- $\sum T^2$ = squared sum values of T

the value of the correlation coefficient lies between

$$-1 \leq l \leq +1$$

here:

- $l = +1 \rightarrow$ Perfect positive correlation
- $l = -1 \rightarrow$ Perfect negative correlation
- $l = 0 \rightarrow$ No linear relationship

The Pearson correlation coefficient is calculated using the Pearson K. structural framework[12].

Table 3.5: Correlation Matrix of Variables

Variable	LA	OC	HB	AN	RP	PB
LA	1.000	0.362	0.542	0.322	0.367	0.512
OC	0.362	1.000	0.321	0.242	0.310	0.545
HB	0.542	0.321	1.000	0.471	0.534	0.342
AN	0.322	0.242	0.471	1.000	0.660	0.311
RP	0.367	0.310	0.534	0.660	1.000	0.436
PB	0.512	0.545	0.342	0.311	0.436	1.000

A heat map was used to visually represent the correlation matrix obtained from Pearson correlation analysis. Different colors indicate varying levels of correlation between variables. Strong positive correlations are represented by darker or warmer colors, while weak or negative correlations are represented by lighter or cooler colors.

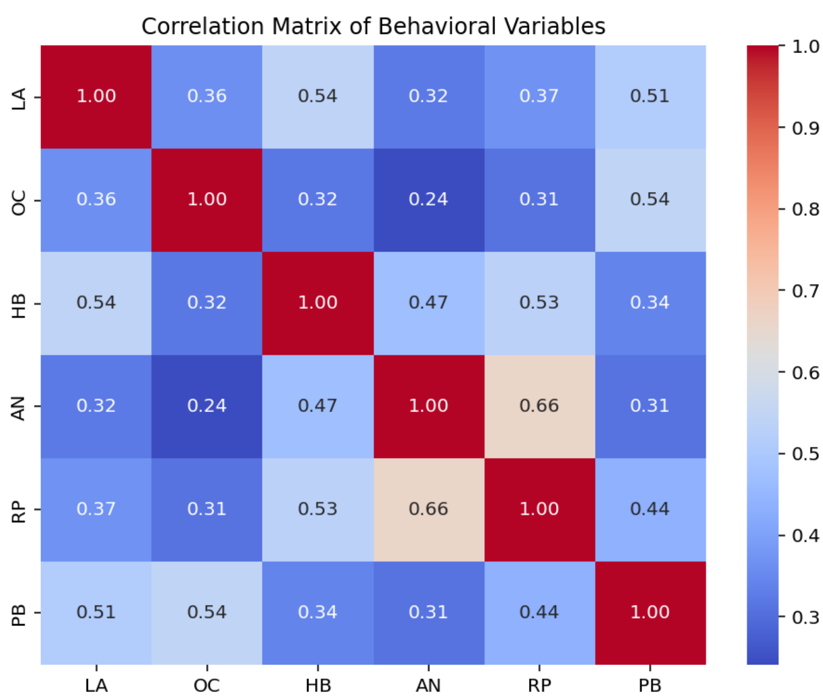


Figure 3.11: Relationship between emotional and psychological bias

3.5 ANOVA Analysis

3.5.1 One-Way Analysis of Variance (ANOVA)

To test for significant differences in behavioral bias ratings between the different education groups,, the numerical computation of one-way analysis of variance (ANOVA) was exercised.

The respondents were classified as follows:

- Undergraduate,
- Graduate,
- Postgraduate.

ANOVA test compares the means of several groups and tests if the difference is statistically significant. The hypotheses tested were:

Null Hypothesis (H_0)

$$H_0 : \mu_1 = \mu_2 = \mu_3$$

No significant difference was observed for education groups in behavioral bias ratings.

Alternative Hypothesis (H_1)

$$H_1 : \text{At least one group mean is different}$$

Scores of behavioral bias varied significantly among education groups. The level of significance for the test was taken as

$$\alpha = 0.05$$

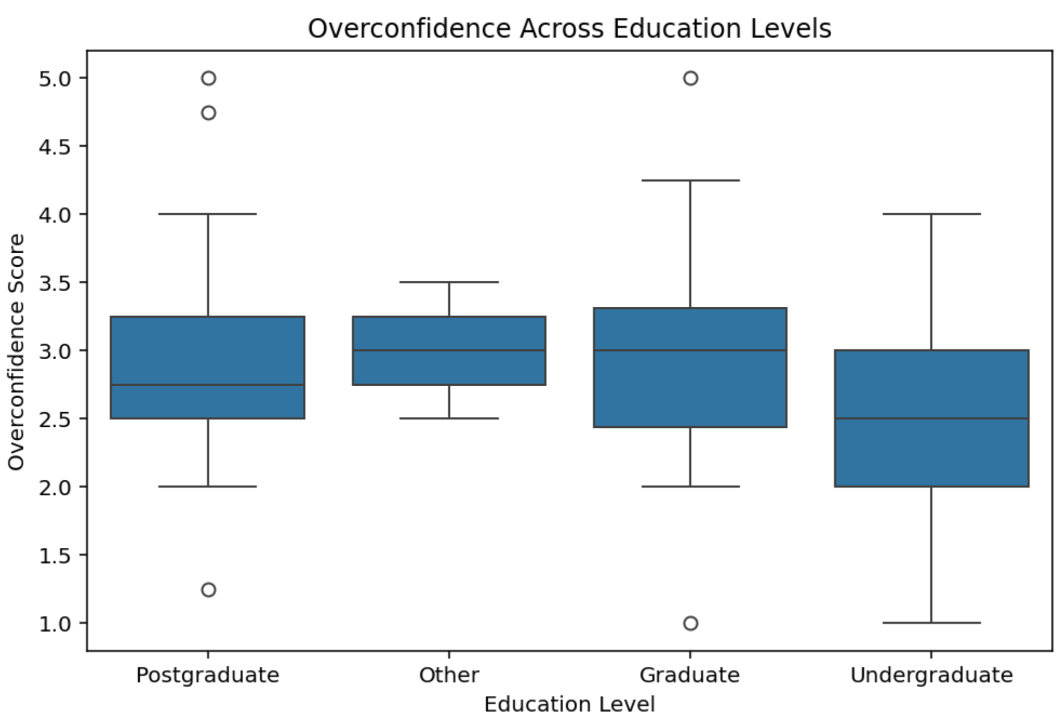


Figure 3.12: Box plots based on education

3.6 Regression Analysis

3.6.1 Multiple Regression Analysis

The altercations of the investors cognitive and emotional errors on their portfolio behavior were explored using multiple regression analysis. It evaluates the link between the dependent and independent variables and also assesses the level to which the behavioral elements influence the investment decisions. In here

- dependent variable is Portfolio Behavior (PB) .
- Independent variables: Loss Aversion (LA), Overconfidence (OC), Herd Behavior (HB), Anchoring Bias (AN), and Risk Perception (RP).

The regression model presented in the study is given by:

$$PB = \iota_0 + \iota_1 LA + \iota_2 OC + \iota_3 HB + \iota_4 AN + \iota_5 RP + \delta$$

where:

- PB = Portfolio Behavior
- ι_0 = Constant,
- $\iota_1, \iota_2, \iota_3, \iota_4, \iota_5$ = Regression Coefficients,
- LA = Loss Aversion,
- OC = Overconfidence,
- HB = Herd Behavior
- AN = Anchoring Bias,
- RP = Risk Perception,
- and δ = error term.

The method was administered to evaluate:

- Regarding the importance of behavior parameters,
- size and direction of their effect on portfolio behavior,
- and the predicted accuracy of the model.

The higher descriptive standards of the regression model were assessed by the determination coefficient (R^2). The statistical significance of such a model and of individual variables was tested by:

- p-values,
- t-statistics,
- and the F-statistic.

The hypotheses for the regression analysis were:

Null Hypothesis (H_0)

$$H_0 : \iota_1 = \iota_2 = \iota_3 = \iota_4 = \iota_5 = 0$$

The portfolio behavior is not considerably affected by the behavioral variables.

Alternative Hypothesis (H_1)

H_1 : Behavioral variables have a core altercations on the behavior of the investor portfolio performances at least with one variab

The measure was computed at a significance level of:

$$\beta = 0.05$$

The regression analysis was performed with Python statistical libraries to test the relation between behavioral finance factors and investor portfolio decisions.

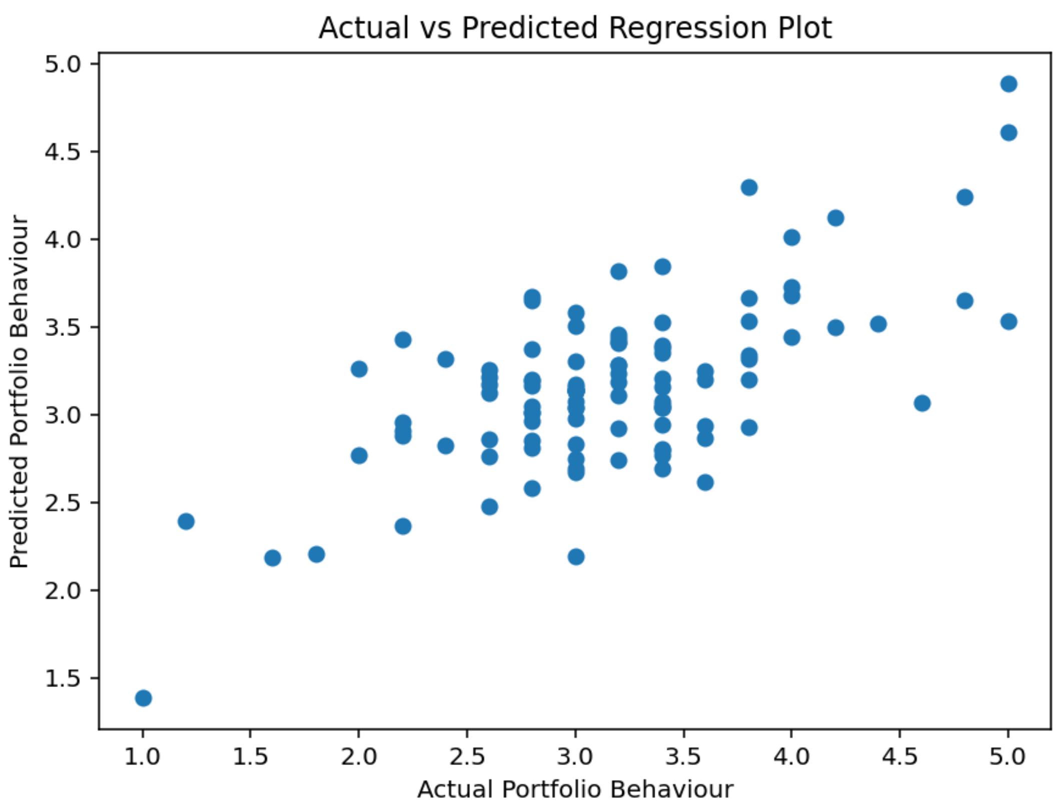


Figure 3.13: Regression Plot for portfolio behavior

Table 3.6: Regression Analysis Results

Variable	Coefficient	p-value	Interpretation
Constant	0.508	0.133	Not significant
Loss Aversion (LA)	0.304	0.000	Significant positive effect
Overconfidence (OC)	0.366	0.000	Significant positive effect
Herd Behaviour (HB)	-0.078	0.374	Not significant
Anchoring Bias (AN)	-0.013	0.906	Not significant
Risk Perception (RP)	0.295	0.020	Significant positive effect

Table 3.7: Model Summary Statistics

Statistic	Value
R-squared	0.452
Adjusted R-squared	0.424
F-statistic	16.33
Prob (F-statistic)	1.01×10^{-11}

3.7 Optimization Analysis

3.7.1 Asset parameter Inputs

This involved defining financial parameters of the six preselected assets; for each asset, two fundamental quantities were determined -

1. Expected annual return
2. Annual standard deviation of returns

these variables are assigned based on long-run historical averages and standard Indian market benchmarks: The risk-free rate is set at 0.06% per annum, consistent with the prevailing Indian repo rate and short-term government yield at this time. This rate serves as the significant contributor in the calculation of the Sharpe ratio.

Table 3.8: Expected Annual Return and Risk of Selected Assets

Asset	Expected Annual Return	Std. Dev. (Risk)
Large-cap equity (Nifty 50)	12%	18%
Mid-cap equity	15%	24%
Government bonds	7%	5%
Gold	10%	16%
Real estate (REITs)	9%	12%
Cash / FD	6%	1%

3.7.2 Construction of Covariance Matrix

Portfolio risk cannot be captured by individual asset volatilities alone; the relationship between assets must also be accounted for. To this end, a 6x6 correlation was constructed, capturing the pairwise linear relationships between all asset returns.

3.7.3 Behavioral Bias Measurement and Normalization

Investor psychological and emotional tendencies such as anchoring bias, risk perception, portfolio behavior, loss aversion, overconfidence, and herd behavior were implemented in this study as the primary psychological biases distorting retail investor asset allocations. Each bias was measured by a detailed structural survey conducted on 105 retail investors with responses registered on a five-point Likert scale. raw mean scores were calculated

Table 3.9: Covariance Matrix of Selected Assets

ASSET	LARGE CAP	MID CAP	GOVTBOND	GOLD	REAL ES	FD
A1 Large-cap	0.0324	0.0367	-0.0009	-0.0014	0.0043	0
A2 Mid-cap	0.0367	0.0576	-0.0010	-0.0115	0.0043	0
A3 Bonds	-0.0009	-0.0010	0.0025	0.0012	0.0006	0.0002
A4 Gold	-0.0014	-0.0115	0.0012	0.0256	0.0015	0.0001
A5 Real Est.	0.0043	0.0043	0.0006	0.0015	0.0144	0.0001
A6 Cash/FD	0	0	0.0002	0.0001	0.0001	0.0001

for each bias and were normalized to a 0-1 scale with

$$\text{Normalized Mean} = \frac{\text{Raw Mean} - 1}{5 - 1}$$

This ensures that biased quantities were expressed as comparable. The resulting normalized scores were as follows: -

Table 3.10: Behavioral Bias Factors and Normalization Scores

Bias Factors	Raw Mean	Normalization Score
Loss aversion	3.0714	0.51785
Overconfidence	2.8190	0.45475
Herd behavior	3.1524	0.53810
Anchoring bias	3.2730	0.56825
Risk perception	3.3105	0.577625
Portfolio behavior	3.2035	0.550875

3.7.4 Distortion Matrix calculation

To translate bias intensities into asset-specific distortions, a theoretical 6x6 distortion matrix was constructed with rows representing the six biases and columns representing the six asset classes. The values for this distortion matrix are based on the normalized behavioral scores obtained from investor responses and are incorporated as adjustment factors to the covariance matrix. Generally they are assumed to be historical averages of Indian standards or derived by authors by conducting surveys and performing computational analysis on the respective information obtained. Summing these contributions across all six biases for each asset yields the total distortion per asset, which is further used to calculate the expected portfolio return incorporated with behavioral biases.

3.7.5 Derivation of portfolio weights

For each portfolio—the traditional portfolio, the biased portfolio, and the behaviorally corrected portfolio—weights were derived through a computational procedure directly in Excel, where the total distortion of each asset respective to each bias acts as a core adjuster in the behaviorally corrected portfolio, and distortion weights were computed for the biased portfolio.

Table 3.11: Behavioral Distortion Matrix

Bias ↓ / Asset →	**Large Cap**	**Mid Cap**	**Bonds**	**Gold**	**REITs**	**FD**
Loss Aversion	-0.5	-0.6	0.5	0.4	-0.2	0.3
Overconfidence	0.4	0.7	-0.4	-0.2	0.2	-0.5
Herd Behavior	0.6	0.5	-0.3	0	0.2	-0.2
Anchoring Bias	-0.2	-0.4	0.2	0.1	0.3	0.2
Risk Perception	-0.4	-0.5	0.6	0.3	-0.1	0.5
Portfolio Behavior	0.3	0.2	-0.1	0	0.4	-0.2

1. For a traditional portfolio, we have an equal-weight baseline. The starting point for all weight calculations was an equal-weight allocation $1/6 \approx 16.67\%$ to each of the six assets. This equal-weight portfolio serves as the neutral, bias-free benchmark — the allocation that a fully rational investor with no prior views and no specific risk-return preferences would hold.

Table 3.12: Initial Equal Asset Weights

Assets	**Weights**
Large-cap	16.67%
Mid-cap equity	16.67%
Bonds	16.67%
Gold	16.67%
Real Estate	16.67%
Cash / FD	16.67%

2. For biased portfolio The normalized bias score for each bias is multiplied by the corresponding distortion coefficient of each asset, producing the distortion contribution matrix. Distortion contributions were summed vertically across all six bias rows for each asset column to yield the aggregated Total Distortion vector

Table 3.13: Distortion Contribution Matrix

BIAS\ASSETS	**Large Cap**	**Mid Cap**	**Bonds**	**Gold**	**REITs**	**FD**
Loss aversion	-0.1554	-0.2590	0.2590	0.1554	0	0.1554
Overconfidence	0.1365	0.2275	-0.2275	0	0	-0.1365
Herd behavior	0.2690	0.1614	-0.1614	0	0	-0.1614
Anchoring bias	-0.1704	-0.1704	0.1714	0.2840	0.1704	0
Risk perception	-0.2890	-0.2890	0.2890	0.1734	0	0.2890
Portfolio behavior	0.2750	0.2750	-0.1650	-0.1650	-0.1650	-0.1650
TOTAL DISTORTION	**-0.1343**	**-0.0545**	**0.1645**	**0.4478**	**0.0054**	**0.1815**

A distortion multiplier was computed for each asset as

$$\text{Multiplier} = (1 + \text{Total Distortion})$$

This multiplier was applied to the equal base weight to produce the raw distorted weight:

$$\text{Raw Distorted Weight} = \text{Base Weight} \times \text{Multiplier}$$

These raw weights were then normalized by dividing each by their sum to ensure the final behavioral weights remain fully invested and sum to one.

Table 3.14: Applying Distortions to Base Weights and Normalization

STEPS	Large Cap	Mid Cap	Bonds	Gold	REITs	FD
Base weight	16.67%	16.67%	16.67%	16.67%	16.67%	16.67%
Total distortion	-0.1343	-0.0545	0.1645	0.4478	0.0054	0.1815
Multiplier	0.8657	0.9455	1.1645	1.4478	1.0054	1.1815
Raw distortion weight	0.14431219	0.15761485	0.19412215	0.24134826	0.16760018	0.19695605
Sum of raw distorted weights	110.195368					
Final normalized weights	0.1310	0.143032192	0.176161806	0.219018516	0.152093671	0.178733511
Shift from base weight	-3.57%	-2.37%	0.95%	5.23%	-1.46%	1.20%

These represent the portfolio that a behaviorally biased Indian retail investor would hold, distorted by the psychological forces measured in the survey.

3. For a behaviorally corrected portfolio
From the very start the behavioral bias was incorporated in the traditional annual expected return by multiplying the total distortion for each asset by every bias factor and then multiplying those values with the original return values to get the new behavioral expected return. Similarly, with a traditional portfolio, the starting point for all weight calculations was an equal-weight allocation $1/6 \approx 16.67\%$ to each of the six assets. This equal-weight portfolio serves as the neutral, bias-free benchmark.

3.7.6 Portfolio metrics computation

For each portfolio—the traditional portfolio, the biased portfolio, and the behaviorally corrected portfolio—the following metrics were computed using the covariance matrix and the respective weight vectors:

1. Portfolio expected return -

$$R_p = \sum_{i=1}^{n} w_i R_i$$

Where:

- R_p = Portfolio Expected Return
- w_i = Weight of asset i
- R_i = Expected return of asset i
- n = Number of assets

a simple weighted average of individual asset returns; they are calculated differently for traditional model, biased model and behaviorally corrected model:-

(a) for traditional model, it is computed simply by multiplying expected annual return with equal weight baseline

(b) for biased model, expected annual return is computed with distorted weight

(c) for a behaviorally corrected model, expected annual weights are computed with total distortion effect of each bias with each asset under consideration to get a behaviorally incorporated expected annual return, which will further be computed with equal weight baseline

2. Portfolio variance – Performed in two steps, first by multiplying weight vectors by the covariance matrix, then by taking the dot product of that result with the weight vector again; these two steps was implemented cell by cell in excel using the covariance rows

$$\sigma_a^2 = \sum_{y=1}^{k}\sum_{z=1}^{k} w_y w_z \mathrm{Cov}(R_y, R_z)$$

Where:

- σ_a^2 = Variance
- w_y, w_z = Asset weights
- $\mathrm{Cov}(R_y, R_z)$ = Covariance between asset returns

3. Portfolio standard deviation - the variance square root

$$\sigma_a = \sqrt{\sigma_a^2}$$

here:

- σ_a = Portfolio Std Dev.
- σ_a^2 = Portfolio Variance

The computation of portfolio standard deviation follows the methodology proposed by Markowitz [5].

4. Sharpe ratio - the core risk-adjusted performance measure

$$U = \frac{R_Y - R_Z}{\sigma_A}$$

Where:

- U = Sharpe Ratio
- R_Y = Portfolio Return
- R_Z = Risk-Free Rate
- σ_A = Portfolio Std Dev.

The computation of Sharpe Ratio follows the methodology proposed by Sharpe, william F. [6]

3.7.7 Behavioral Portfolio Optimization

1. GRG Solver — Run 1 Having established considered asset annual expected return for each asset along with allocated initial weight, portfolio expected return for traditional model and biased portfolio with its new distorted weights, the next study computed the rational benchmark

(a) The portfolio that maximizes the sharpe Ratio without any behavioral distortion
The Excel Solver was configured as follows: the objective was set to maximize the cell containing the Sharpe Ratio, while the decision variables were the six portfolio weights and the three constraint sets

were applied. The GRG Nonlinear engine was selected with Multistart enabled, a population size of 100, forward-difference derivatives, and a convergence tolerance of 0.0001. The solver completed 140 subproblem iterations over 3.92 seconds and converged to a global solution. The optimal weights produced were:

Objective Cell (Max)

Cell	Name	Original Value	Final Value
B87	SHARPE RATIO LARGE CAP	1.427751092	1.427751092

Variable Cells

Cell	Name	Original Value	Final Value	Integer
E73	PORTFOLIO EXPECT RTN GOLD	0.1667	0.085266972	Contin
E74	GOLD	0.1667	0.108455299	Contin
E75	Compute W × Σ first GOLD	0.1667	0.196542863	Contin
E76	(intermediate vector): GOLD	0.1667	0.284453996	Contin
E77	W*COV_A1 GOLD	0.1667	0.185964756	Contin
E78	W*COV_A2 GOLD	0.1667	0.139514063	Contin

Figure 3.14: Excel Solver Output for Behavioural Portfolio Optimization

This solution represents the theoretically optimal allocation for an investor with no behavioral biases—the rational efficient frontier solution for this six-asset universe.

(b) Wealth accumulation: optimal vs biased portfolio to translate the annual return difference into tangible financial consequences, a compound growth wealth projection was constructed for an initial investment of Rs 100,000 across eight time horizons: 1, 3, 5, 10, 15, 20, 25, and 30 years. Wealth at each horizon was computed using the formula:

$$FinalWealth = InitialInvestment(1 + PortfolioReturn)n$$

applied separately to the biased portfolio (return = 9.67%) and the optimal portfolio (return = 9.92%).

The resulting wealth trajectories reveal the following key findings:

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Table 3.15: Wealth Projection Across Time Horizons

Years	Biased Wealth	Optimal Wealth	Wealth Gap	% Gap
1	109671.3550	109918.6500	247.2950	0.0022498
3	131910.5793	132804.9178	894.3384852	0.006734227
5	158659.4872	160456.3575	1796.8703120	0.011198499
10	251728.3288	257462.4266	5734.0978730	0.022271591
15	399390.8755	413114.8317	13723.9561900	0.033220681
20	633671.5150	662869.0113	29197.4962800	0.044047158
25	1005379.9760	1063615.4710	58235.4943400	0.054752395
30	1595130.7150	1706638.6420	111507.9273000	0.065337749

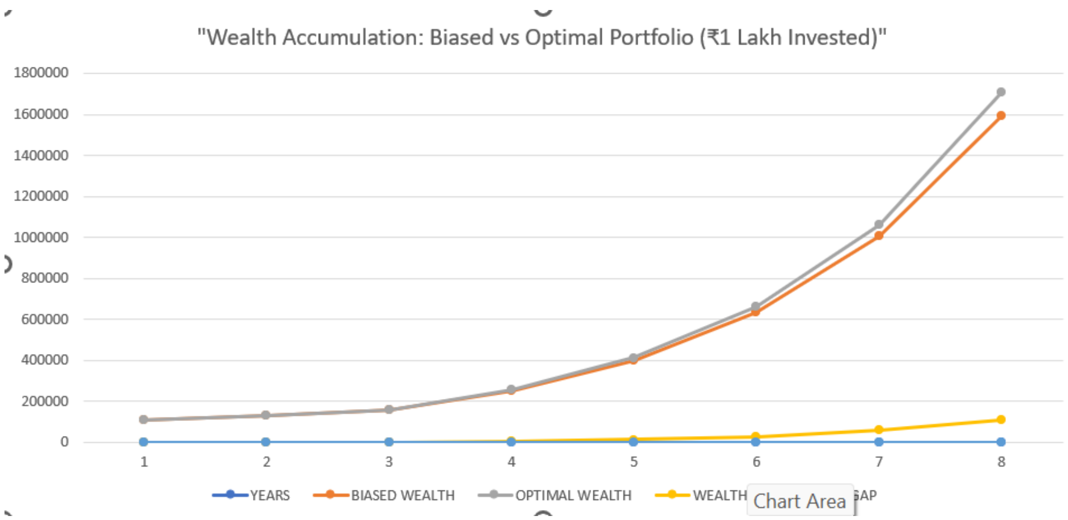

Figure 3.15: Wealth Accumulation: Biased vs Optimal Portfolio

These projections demonstrate that the financial cost of behavioral bias is non-linear and accelerates dramatically with the investment horizon due to compounding. A bias-induced return deficit of just 0.25% per annum destroys 2.23% of optimal wealth over ten years and 6.53% over thirty years—representing a cumulative wealth loss of over Rs 1.11 lakh on a Rs 1 lakh initial investment.

2. GRG Solver—Run 2: Having established considered asset annual expected return for each asset along with allocated initial weight, portfolio expected return for traditional model and biased portfolio with its new behaviorally adjusted expected return obtained by original traditional model adjusted weight with total distortion of each bias with every asset under consideration, the next study computed the rational benchmark

   (a) The portfolio that maximizes the sharpe Ratio with behavioral distortion under accountability
   The Excel Solver was configured as follows: the objective was set to maximize the cell encompassing the Sharpe Ratio, while the decision variables were the six portfolio weights and the set of restriction

barriers were applied. The GRG Nonlinear engine was selected with Multistart enabled, a population size of 100, forward-difference derivatives, and a convergence tolerance of 0.0001. The solver completed 135 subproblem iterations over 4.80 seconds and converged to a global solution. The optimal weights produced were:

Objective Cell (Max)

Cell	Name	Original Value	Final Value
E121	sharpe ratio	0.623121312	0.623121312

Variable Cells

Cell	Name	Original Value	Final Value	Integer
F121	weights	0.1667	0.266555339	Contin
F122	weights	0.1667	0.128355491	Contin
F123	lambda= weights	0.1667	0.11337463	Contin
F124	BEHAVIOURAL weights	0.1667	0.06057553	Contin
F125	weights	0.1667	0.258393666	Contin
F126	weights	0.1667	0.172945344	Contin

Figure 3.16: Excel Solver Output for Sharpe Ratio Optimization

(b) Traditional vs. Behaviorally Corrected Wealth Comparison
A final comparative analysis was conducted between the traditional (equal-weight optimal) portfolio and the behaviorally corrected portfolio derived. Using the behaviorally corrected return and traditional return, the wealth projection was extended across the same eight time horizons:

Table 3.16: Traditional vs. Behavioral Wealth Projection

Years	Traditional	Behavioral
1	109918.6500	110656.9226
3	132804.9178	135498.8985
5	160456.3575	165917.7851
10	257462.4266	275287.1141
15	413114.8317	456750.2822
20	662869.0113	757829.9516
25	1063615.4710	1257374.6700
30	1706638.6420	2086208.2030

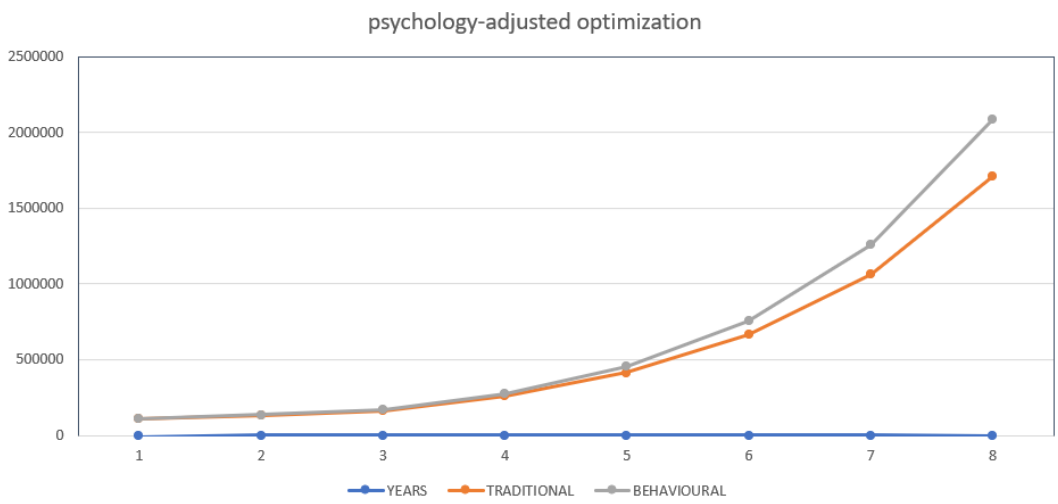

Figure 3.17: Psychology-Adjusted Portfolio Optimization

These results confirm that explicitly correcting for behavioral bias through the behavior return-adjusted optimization yields substantially superior long-run wealth outcomes compared even to the standard rational optimization. The behaviorally-corrected portfolio outperforms the traditional optimal by Rs 3.79 lakh at a 30-year horizon, underscoring the practical value of incorporating adjustment into the portfolio construction process.

Chapter 4

Results and Discussion

The following section deals with the interpretation of the survey data examined from 105 respondents using different statistical tools. The results are discussed to comprehend the effect of personal prejudices on investor portfolio performance and final decision-making.

4.1 Descriptive Statistics Analysis

Descriptive statistics were employed to describe the demographic profile and behavioral tendencies among the population included in this study. The survey was conducted on 105 valid responses, and the effect of emotions on portfolio behavior and taking decisions financially was analyzed.

The data depicted that the large section of subjects was from the 18-25 age profile and were mainly novice investors with little to no investment experience. Most of the respondents were in favor of investments in stocks and mutual funds and identified wealth creation as the main investment objective.

The analysis of behavioral factors showed that risk perception has the highest mean score among all behavioral biases, which indicates that the investors are particularly sensitive to the prospect of taking risk and are cautious while proceeding in an uncertain market, which is relevant to the foundation of prospect finance theory.

Furthermore, the mean score for anchoring bias was rather high, indicating that many investors depend to a great extent on the initial information cue to make resolutions instead of evaluating current fundamentals.

Moderate values of portfolio behavior are an indication that respondents are influenced by market trends, societal opinions, and actions of other investors.

Overall, data verified a pronounced psychological and behavioral influence on investors' decision-making and portfolio management behavior. The results confirm the assumptions of the behavioral finance theory that certain factors can make investors act irrationally in making financial decisions.

4.2 Normality Analysis

The results of this analysis with the help of the Shapiro-Wilk test showed that some variables are not strictly normally distributed, as the p-value is < 0.05. However, we took all variables under consideration, as the skewness values were within acceptable limits, depicting fairly symmetric and not highly distorted distributions.

Similarly, most of the kurtosis values were in acceptable ranges, indicating that the variables did not show extreme peakedness or flatness. Risk Perception (RP) had a relatively higher value of kurtosis, but the deviation was not significant enough to affect the validity of further statistical analysis.

The data were from 105 respondents; some deviated from strict normality conditions, but the Central Limit Theorem supports the assumption of approximate normality. Therefore, the data were considered appropriate for the application of further parametric statistical techniques.

The normality analysis as a whole shows that the behavioral variables are distributed appropriately for the next statistical analysis in the study.

4.3 Correlation Analysis

The correlations depict a significant positive association between behavioral factors and portfolio behavior.

The study underscores that loss aversion (LA) and portfolio behavior (PB) are positively correlated (r=0.512), illustrating the phenomenon that investors exhibiting higher loss aversion are likely to be cautious in portfolio behavior. Moreover, overconfidence (OC) and portfolio behavior have the highest correlation (r=0.545), which means that very confident financiers are more engaged in investing and portfolio management. Herd behavior (HB) had a fairly positive association with risk perception (RP) (r=0.534), showing that the investors affected by the market trend are greatly affected by the market risk perceived. The anchoring bias (AN) had a strong positive effect on risk perception (r = 0.660), on account of the fact that investors who base their decisions on previous data and reference points tend to perceive market risk more strongly. Portfolio Behavior (PB) was positively associated with all the behavioral variables. It reconfirms that psychological factors have a substantial impact on investment decisions. None of the correlation coefficients exceeded 0.90, pointing to the absence of greater multicollinearity between the independent variables. Thus, the variables were considered appropriate for regression analysis.

4.4 Interpretation of ANOVA Analysis

To figure out whether overconfidence is affected by the level of education, i.e., undergraduate, graduate, and postgraduate, a one-way ANOVA was performed.

The outputs showed an F statistic of 2.288 and a p-value of 0.107, which is $>$ 0.05, and therefore, we were not able to reject the null hypothesis.

This showed that there does not exist a statistically significant difference in overconfidence levels with different education backgrounds; i.e., it does not exert a significant effect on investor overconfidence and financial commitments.

Often, it has been seen that literacy knowledge does have an effect on decision-making, not primarily but supportively, but our primary respondents are from an age group of 18-25 years with similar education levels; thus, the results imply the same.

Overall, on the basis of ANOVA analysis, the overconfidence behaviour is moderately stable between respondents irrespective of their educational level.

4.5 Regression Analysis

The regression model produced a R^2 value of 0.452, demonstrating that approximately 45.2% of all fluctuation in portfolio behavior is illustrated by the behavioral biases and factors included in the study.

The F-statistic is statistically significant ($p<0.05$), depicting that the overall regression structure is valid and suitable for explaining portfolio behavior.

1. There exists a statistically significant positive effect of loss aversion on portfolio behavior ($\beta = 0.304$, $p < 0.05$).Resulting in investors who are more sensitive to losses, they tend to make careful and emotionally affected investment decisions.
2. It also demonstrates a substantial positive relationship of overconfidence with portfolio behaviour, ($\beta = 0.366$, $p < 0.05$) which reveals that investors having a highly confident nature are more actively involved in investment activities and portfolio management decision-making.
3. A negative and meagre relationship of herd behavior in association with portfolio behavior ($p > 0.05$). Although some investors follow market trends and crowd behaviour, the effect of herd behavior was not a major determinant of portfolio decision-making in the structural framework.
4. Anchoring biases have an insignificant impact on portfolio behavior ($p > 0.05$). It does not indicate that dependence on past information or reference points impactfully affects portfolio decision-making among respondents.
5. A statistically significant positive effect is exhibited by risk perception towards portfolio behaviour, ($\beta = 0.295$, $p < 0.05$) which illustrates that along with higher awareness of market risk factors, an investor tends to make more structured and careful portfolio decisions.

4.6 Optimization Analysis

The significance of optimization analysis and frameworks under this study is that they make two distinct contributions to portfolio performance management. First, it demonstrates – using a concrete numerical framework – that the financial cost of behavioral bias compounds significantly over time. Second, it operationalizes behavioral finance theory by translating qualitative bias concepts into quantitative distortion coefficients that can be directly incorporated into an optimization model.

Survey Results and Normalization

The structured survey administered to 105 retail investors yielded raw mean scores for each of the six selected behavioral biases. The result that all six biases fall within the Moderate band indicates that Indian retail investors do not exhibit extreme psychological distortions. Risk perception registers the highest normalized score (0.5776), suggesting that retail investors in India systematically overestimate the danger of volatile asset classes. Overconfidence records the lowest score (0.4547), which runs counter to global literature that typically identifies overconfidence as the dominant retail investor bias.
The survey confirmed that all six behavioral biases are consistently present at moderate intensity levels among Indian retail investors.

Distortion Matrix Weight Perturbations

The representative distortion matrix indicates that gold receives the largest positive distortion of $+0.4478$, driven by risk perception, anchoring bias, and loss aversion. The result corroborates a long-observed behavioral phenomenon in Indian household finance: gold consistently receives a disproportionate share of retail investor portfolios far beyond what mean-variance optimization would justify, whereas large-cap equity records the most

Table 4.1: Behavioural Distortions Across Asset Classes

Asset Class	Distortion	Final Weight (%)	Allocation Change
Gold	+0.4478	21.90	+5.23
Large-Cap Equity	-0.1343	13.10	-3.57
Mid-Cap Equity	-0.0237	14.30	-2.37
Cash/FD	+0.1815	17.87	+1.20
Government Bonds	+0.1645	17.62	+0.95
REITs	+0.0054	15.21	Near Neutral

negative total distortion of -0.1343, driven by loss aversion and risk perception. the result states that large-cap equity offers the most liquid and efficient access to Indian economic growth

GRG solver Run-1, & Run-2

The GRG nonlinear optimization solver (for Run-1 and & Run-2) in Microsoft Excel provided optimal weight allocation for the assets under consideration, each for the traditional model and the behaviorally corrected model, which optimizes portfolio performance by minimizing risk and maximizing return (maximizing Sharpe ratio) .This enables an investor to make more structured and careful portfolio decision-making.

Chapter 5

Conclusion And Future Scope

The research suggests that psychological factors are important in the planning of financial investments and in the performance of portfolios. These results show the advantages of including behavioral inputs in traditional models to improve their predictive accuracy and to obtain a more complete understanding of the portfolios of investors. Our hypothesis regarding the affect of behavioral attributes of a person affecting their financial investment decisions was accepted, which in turn gave distorted results and hence affecting optimal results

Further discussions include precautionary steps for investors such as constantly examining and understanding the causes and effects of investors' emotional and cognitive errors and learning how to reduce or overcome them. Furthermore, it is recommended to collect and analyze metrics and data from different sources instead of a limited one. Investors should be able to analyze objectively and without personal feelings or bias their own investing capabilities. Getting over cognitive challenges or emotional discomforts can be helped by professional help or feedback. Studying the investment tactics and life experiences of great investors can be invaluable. Moreover, the optimization techniques for assessing the biases by changing the objective function are multiple, such as by maximizing the expected returns or by maximizing the Sharpe ratio. Researchers can use any of these frameworks to reach the desired output. Some constraints can be used for maximum allocation or for target return, which would further restrict the optimization process for weight allocation for assets under consideration.

Therefore, this thesis concludes that behavioral finance reflects in the investor's portfolio decision-making. Future studies are required to follow up on the role of artificial intelligence and big data analytics. Machine learning and natural language processing, as they are emerging digital innovations, may automate behavioral, cognitive, and emotional factor measurement and adaptive optimization. Estimate distortion coefficients empirically from real investor portfolio data. Future work should explore sensitivity analysis across different λ values incorporated while calculating portfolio returns. Another area of research in behavioral finance could be cross-cultural differences in perceptual biases and their implications. Future models may include international assets, commodities, and alternative investments. Also, judgement biases in market analysis are amenable to more accurate prediction and portfolio performance.

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