

Exploring the Impact of Behavioral Biases, Emotional Factors, and Financial Awareness on Investment Decisions: Evidence from Indian Investors

Praveen Kumar Verma¹ | CA Arya Rastogi^{2*} | CA Jayendra Malhotra³

¹Assistant Professor, G L Bajaj Institute of Technology and Management, Greater Noida, Uttar Pradesh, India.

²Guest Professor, Jesus and Marry College, University of Delhi, Delhi.

³Research Scholar, ACCF, Amity University, UP, India.

*Corresponding Author: caaryarastogi@gmail.com

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ABSTRACT

The present study examines the complex interconnection between behavioural biases, emotions, and investment decision-making process in India. The current research uses the concepts of behavioral finance in order to illustrate the influence of cognitive and emotional factors on the investment process, which leads to inefficient outcomes contrary to the classic finance approaches, which usually consider people rational. In total, 525 individual investors with various demographic characteristics and investment experience were selected for the study using a standardized questionnaire. The study uses descriptive statistics, correlation analysis, chi-squared tests, and binary logistic regression in order to examine the impact of overconfidence, loss aversion, herding behavior, emotional volatility, and financial awareness on risk tolerance. The research shows that key demographic factors such as age and gender have a significant effect on the investment process. Behavioural biases, such as overconfidence and loss aversion, are widely spread and have a significant effect on risk tolerance. Emotional factors, especially anxiety and fear, negatively correlate with the ability to take risks. In addition, the knowledge of the behavioral finance theory and consulting with financial advisers positively affect rational investment decision-making. Implications of the findings lie in the necessity for development of improved investor education initiatives which would include principles of emotional intelligence and behavioral finance. In addition, the findings have practical implications for financial advisors, regulators, and fintech developers when designing behavior-based investments solutions. Although the study had limitations in non-random sampling and using self-reporting data, this research is a good basis for further studies and demonstrates the importance of taking into consideration psychological factors in investment strategies in developing countries like India.

Keywords: Behavioral Finance, Investor Psychology, Risk Tolerance, Emotional Impact, Financial Awareness, Investment Decision-Making, India.

Introduction

However, the past decade has seen an upsurge in the importance of behavioral finance in both scholarly and practitioner circles in investment discussion. Classical financial theories, primarily founded on Efficient Market Hypothesis (EMH) proposed by Fama (1970), are premised on the notion of a rational man who acts based on all available information. However, evidence from reality has persistently challenged this notion of an irrational man whose actions are driven by psychological and emotional biases (Shiller, 2003). This is where behavioral finance comes in by bridging the gap using psychology and sociology.

Given its large middle class population, greater financial inclusion, and rapid financial digitization, India provides an ideal ground for studying investor behaviors from the angle of behavioral finance. In the past ten years, millions of regular Indian investors have participated in the capital markets via investment avenues such as mutual fund, direct equity, cryptocurrency exchanges, and robo advisors. Financial access, which may be considered progressive, makes investors vulnerable to cognitive and emotional biases (SEBI, 2020).

Behavioral biases are biases that are contrary to rational thinking and affect one's judgment and decision-making process. The study will explore some of the major biases, such as the overconfidence bias, loss aversion, herding behavior, and the disposition effect. Overconfidence bias is an irrational assumption of investors regarding themselves as knowing too much or having a great influence on outcomes, usually leading to over-trading (Barber & Odean, 2001). Loss aversion refers to the tendency to focus more on avoiding losses than gaining the same amount (Tversky & Kahneman, 1991). Herding behavior is the replication of actions by individuals, particularly in circumstances that are not clear (Bikhchandani et al., 1992). The disposition effect is the tendency to sell winners early and hold losers (Shefrin & Statman, 1985).

Besides cognitive biases, emotions and other psychological factors play a significant role in shaping investment decisions. Emotions like fear, greed, hope, and regret can cloud one's judgment and make impulsive and irrational financial decisions (Loewenstein et al., 2001). Combining affective science and finance behavior studies has produced the theory of dual process, which posits that instinctual emotional mechanism often prevails over rational judgment in financial matters (Stanovich & West, 2000).

Social factors, particularly through the use of digital media, have made the investment decision process even more complex. Today's investors are constantly bombarded with financial information, ideas, and trends which affect their views and lead to herd behavior (Chen et al., 2014). The advent of algorithmic news and the proliferation of financial advice given by influencers makes it difficult for people to distinguish between useful information and noise.

Financial intelligence and knowledge of behavioral finance can help fight against these biases. According to Lusardi and Mitchell (2014), individuals who have high levels of financial literacy tend to plan for retirement, diversify their investments, and avoid expensive borrowings. Hackethal et al. (2012) found out that financial advisors are vital in addressing investor biases and improving their performance. In India, the Securities and Exchange Board of India (SEBI) has taken many steps in order to educate financially; however, the reach and impact of behavioral finance are limited.

Although there is increasing academic attention paid to this area, empirical studies carried out in India that have tried to explore the relationship between cognitive biases, emotions, and financial awareness of retail investors are few in number. This paper attempts to fill this void by analyzing the impact of demographic attributes, psychological attributes, and financial knowledge on risk tolerance and investment decisions. The data for this study consists of 525 valid responses collected through a structured questionnaire and includes descriptive analysis, chi-square tests, correlation analysis, and logistic regression.

The specific objectives of this study include:

- Determining the effect of demographic variables such as age, gender, income, and education level on risk tolerance levels of investors.
- Determine the prevalence rate of any important behavioral biases and how they affect the investment preferences of investors.
- Determining the effect of emotional variables and the use of social media on risk taking in finance.
- Determine the effect of behavioral finance knowledge in reducing cognitive biases.
- Determine if involvement of investors in financial advisory leads to better investment decisions.

This research adds to the literature on behavioral finance and contributes to the field by achieving the above stated objectives. The findings from this study shall be useful in designing better behavioral nudges, financial advisory tools, and investor education programs that target the unique behavior of Indian investors.

Literature Review

There have been tremendous developments in behavioral finance within the last four decades, which offer alternative explanations of the theories of rational choice models and the efficient market hypothesis, which form the basis of conventional finance theory. The field of behavioral finance, based on the work of Kahneman & Tversky (1979) and Thaler (1980), uses psychological perspectives to provide an understanding of why investors' choices differ from those considered to be rational. This review of the literature summarizes recent research in behavioral finance.

Evolution of Behavioral Finance

The formulation of Prospect Theory by Kahneman and Tversky (1979) set up the foundation of behavioral finance theory since the asymmetry of perception of gain and loss was observed where the former seemed more impactful compared to latter. This bias was later confirmed using empirical data across a number of financial instances (Tversky & Kahneman, 1992; Benartzi & Thaler, 1995). Thaler (1985) further developed the paradigm by creating a mental accounting concept which describes how people allocate their finances and make decisions separately. Such paradigms disputed the principles of utility maximization and effective processing of information which lie at the core of classic finance theory (Fama, 1970).

Key Behavioral Biases

There is a number of known behavioral biases which influence the decision making of investors. The bias of overconfidence, when a person feels that his/her knowledge or predictions are superior to those of anyone else, may lead to excessive trading and ineffective management of portfolios (Barber & Odean, 2001). It was proved by Glaser and Weber (2007) that overconfident people tend to underestimate the risks and overestimate the profitability, thus insufficiently diversifying their portfolios.

The disposition effect involves the tendency to prematurely sell winning investments and hold on to losing investments for long periods, and is analyzed in studies carried out by Shefrin and Statman (1985) and Odean (1998). They both find emotional reactions to realized profits and losses as important factors here. This bias is closely related to loss aversion, where the fear of realizing a loss outweighs any reason for changing portfolio allocation (Genesove & Mayer, 2001).

Herding bias refers to the behavior of people following the majority, particularly in situations of uncertainty. Bikhchandani, Hirshleifer, and Welch (1992) have developed a theory on informational cascades, explaining why rational people choose to imitate others because of asymmetric information. Empirical evidence supporting herding was provided by Nofsinger and Sias (1999) and Welch (2000). Herding often leads to financial bubbles and crashes.

Anchoring is a form of cognitive bias where individuals tend to heavily rely on the first information available (Anchor) while making decisions (Tversky & Kahneman, 1974). In research conducted by Kaustia, Alho, and Puttonen (2008), it has been shown that financial experts are subject to the anchoring bias while making profit estimates.

Emotional and Psychological Factors

More and more, emotions like fear, greed, hope, and regret are becoming an integral element of behavioral finance. According to Loewenstein et al. (2001), there exists a "risk-as-feelings" theory suggesting that people's emotions often precede their rational assessments and are able to dominate them. This idea is supported by neurofinance experiments carried out by Shiv et al. (2005). In particular, it was proven that people who experience damage to the brain's emotional centers make more rational and consistent decisions.

Slovic et al. (2002) offered affect theory that pointed out that the emotional valence, whether the person experiences positive or negative emotions, strongly affects the risk perception. In the case when people feel positively, they underestimate risks, but in case people feel fear or are worried, they avoid any reasonable opportunities. Such emotional volatility may cause impulsive actions on the market both during the bull and bear periods (Ackert & Deaves, 2010).

Locus of control, the psychological feature determining how people relate the events to themselves and to other people, greatly affects financial decisions. The studies performed by Rotter (1966) and Perry and Morris (2005) proved that people who had an internal locus of control were more likely to perform reasonable and long term planning.

Financial Literacy and Behavioral Awareness

Several studies have confirmed the role played by financial literacy in reducing the vulnerability to behavioral biases. Lusardi and Mitchell (2014) argued that knowledge on financial principles leads to diversification, planning and risk-taking. In addition, Van Rooij et al. (2011) have observed a strong relationship between financial literacy and participation in stock market trading.

Knowledge on behavioral finance has proved to be effective in improving investors' decisions. Ricciardi & Simon (2000) argued that knowledge on common biases enables an individual to avoid making emotional decisions. The research conducted by Montier (2002) and Pompian (2012) proposed that there was need for customized behavioral profiles to enable financial advisors to counter the prejudices of their clients.

In India, Bhushan & Medury (2013) found out that the level of financial literacy was low, particularly among the young and rural investors. However, behavioral awareness is significantly lower. According to Roy & Basu (2020), behavioral finance education improves investment returns and confidence among Indian retail investors.

Role of Financial Advisors

Financial consultants can substantially help in minimizing behavioral biases. Hackethal et al. (2012) found out that financial consultants act as the "behavioral buffer" and stop clients from taking emotional decisions. The effectiveness of the financial consultants relies upon the extent to which they have knowledge about behavioral finance and ability to gain trust (Gennaioli, Shleifer, & Vishny, 2015).

Access to reliable financial advisory services remains a concern for developing countries, such as India. Chattopadhyay and Dasgupta (2019) found that even though advisors affect decision making, many investors still rely on informal advisors, such as family members, friends, or social media.

Digital Finance, Social Media, and Fintech Platforms

The rise of fintech apps and algorithmic financial applications has created some new behavioral patterns. The study done by Banerjee & Banerjee (2020) and Jurek & Yang (2021) explored how the application design, default settings, and push notifications affect the user behavior. Chen et al. (2014) showed that ideas spread through the social media can lead to crowd behavior, particularly in young and inexperienced investors.

Nudges—an implicit message embedded into digital platforms—have increasingly become a tool for affecting user behavior. Thaler & Sunstein (2008) put forward the concept of "libertarian paternalism," whereby people are encouraged to make better choices without any coercion. In finance, the nudges could be represented by automatic savings notifications, portfolio rebalance prompts, or behavioral nudges.

Gender and Demographic Influences

Gender, age, income, and educational levels have been found to impact the extent and nature of behavioral biases. Barber and Odean (2001) found that men tend to be more overconfident than women, hence trading more often but earning less. Bajtelsmit and Bernasek (2001) found that women tend to be more risk-averse and engage in long-term and diversified investments.

Age and experience have also been found to impact the vulnerability to bias. While young investors have more technological skills, they tend to be easily influenced by their peers' viewpoints and technological developments (Gao, Lin, & Sias, 2017). Older investors have been found to be more averse to losses and to be more cautious about selecting their portfolios (Korniotis & Kumar, 2011).

Educational levels improve cognitive functions and reduce the reliance on heuristics (Agarwal et al., 2009). However, even highly educated people have not been found to be immune from biases, as seen in research showing behavioral mistakes among financial practitioners when under pressure (Coval & Shumway, 2005).

Research Gaps and Future Directions

However, although there is no shortage of research done on behavioral biases and emotional finance, there are some critical gaps that remain, particularly in emerging nations like India. There is little to no research that fully explores the interplay between bias, emotion, financial literacy, and advisory interventions in a comprehensive way. In addition, the bulk of research utilizes cross-sectional data, which limits causal inference.

There is a lack of research that is sensitive towards gender issues and is contextually appropriate. The impact of fintech and social media on behavioral finance is underexplored, especially from a non-Western perspective. At the moment, empirical evidence linking behavioral interventions, such as nudges or profiled advice, with improved financial outcomes is at an early stage.

Research Methodology

This part defines the methodological framework, data gathering methodology, sample profile, hypotheses, and tools used in this research. The methodological approach is designed to provide a full understanding of the behavioral and emotional factors influencing investor decisions.

Research Design

The methodology used in this study includes a quantitative approach through the use of a structured questionnaire for collecting primary data. The research is both descriptive and exploratory in nature, seeking to establish patterns, relationships, and basic processes affecting financial decision making.

Population and Sampling

The intended population for the study comprises individual investors with different socio-economic statuses in India. Through purposive and snowball sampling, 525 usable answers were gathered. Selection of respondents was based on their participation in financial markets such as stocks, mutual funds, insurance or online investment services).

Data Collection Instrument

A systematic questionnaire was created and disseminated digitally using Google Forms, delivered through email and social media sites. The questionnaire consisted of five sections:

- Section A: Demographic Data (Age, Gender, Education, Income, etc.)
- Section B: Investment Preferences and Risk Tolerance
- Section C: Indicators of Behavioral Bias (e.g., overconfidence, loss aversion, disposition effect, herding)
- Section: D: Emotional and Psychological Dimensions (e.g., emotional repercussions, dread, trepidation, exhilaration)
- Section E: Cognizance and Application of Behavioral Finance Principles and Financial Advisors

All items were assessed utilizing a 5-point Likert scale (ranging from 1 = Strongly Disagree to 5 = Strongly Agree).

Variables and Constructs

- **Dependent Variable**
 - Risk Tolerance (Low vs High)
- **Independent Variables**
 - Demographics: Age, Gender, Income, Education
 - Behavioral Biases: Overconfidence, Loss Aversion, Herding, Disposition Effect
 - Emotional Traits: Anxiety, Fear, Excitement, Confidence
 - Awareness: Behavioral Finance Knowledge, Use of Financial Advisors

Research Hypotheses

The following hypotheses were developed based on literature and theoretical frameworks:

- H1:** There is a significant relationship between demographic variables and risk tolerance among investors.
- H2:** Behavioral biases (overconfidence, disposition effect, herding behavior, and loss aversion) significantly influence investor risk tolerance.
- H3:** Emotional factors (e.g., fear, excitement, confidence) significantly influence investor decision-making and risk perception.
- H4:** Higher awareness of behavioral finance principles is associated with more rational investment decisions.

H5: Consultation with financial advisors positively moderates the impact of behavioral biases on investment decisions.

Data Analysis Techniques

To examine the research hypotheses, the following **statistical techniques** were used:

- **Descriptive Statistics:** To summarize demographic data and general behavioral trends
- **Chi-square Tests:** To identify associations between categorical variables (e.g., gender and risk tolerance)
- **Correlation Analysis:** To assess the strength and direction of relationships among behavioral and emotional variables
- **Binary Logistic Regression:** Used to determine the predictors of investor risk tolerance (dependent variable = low/high)

These analyses were conducted using **IBM SPSS Statistics (v26)**.

- **Ethical Considerations:** Participants were informed of the purpose of the study, and anonymity and confidentiality were maintained. Participation was voluntary, and respondents had the option to withdraw at any time.

Data Analysis and Results

The result of the statistical analysis carried out on data obtained from 525 legitimate respondents. The analysis includes descriptive statistics, inferential analysis (chi-square analysis and correlation) and logistic regression analysis in order to test the formulated hypotheses. Visualization tools such as bar graphs, pie graphs and boxplot are used to make interpretation easier.

The statistical analysis has led to very important discoveries in the behavioral, emotional and information factors that drive the investment decisions of investors in India. These interpretations confirm the formulated hypotheses and have very important implications for both academic and practical usage.

• Demographic Impact on Risk Tolerance (H1)

Chi-square analysis revealed strong correlations between investor demographic characteristics and their risk tolerance level. Gender ($\chi^2 = 9.83$, $p = 0.002$) and age ($\chi^2 = 11.12$, $p = 0.011$) were highly influential when it came to managing and perceiving risks. Males and younger investors were more likely to engage in high-risk investments, which conforms to previous research findings (Barber & Odean, 2001). This confirms the fact that the appetite for risk is strongly influenced by biological, psychological and experience related characteristics of age and gender. This confirms H1, that demographics influence risk tolerance. Table 1 shows the demographic characteristics:

Table 1: Demographic Profile of Respondents (N=525)

Variable	Categories	Frequency	Percentage
Gender	Male	305	58.1%
	Female	220	41.9%
Age Group	18–25	160	30.5%
	26–35	200	38.1%
	36–50	120	22.9%
	51+	45	8.6%
Education Level	Undergraduate	190	36.2%
	Postgraduate	280	53.3%
	Doctorate/Professional	55	10.5%
Monthly Income	< ₹25,000	120	22.9%
	₹25,000–₹50,000	195	37.1%
	> ₹50,000	210	40.0%

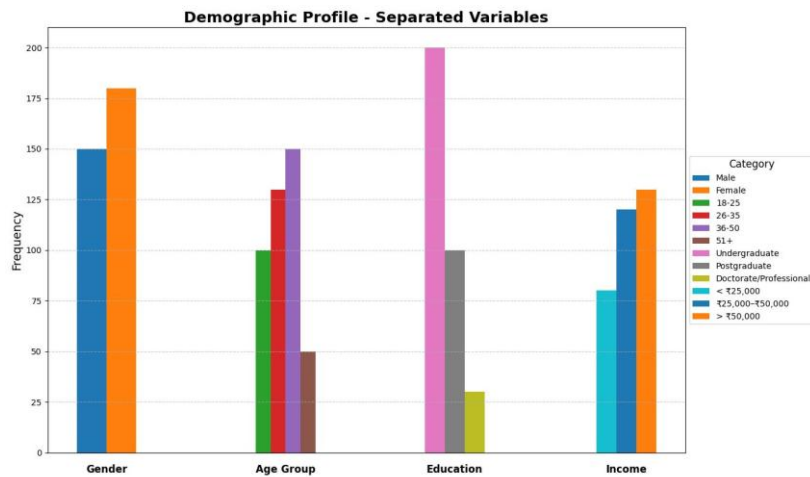


Figure-1: Demographic distribution of respondent

• Behavioral Biases and Risk Behavior (H2)

The descriptive statistics and regression analyses confirmed that biases such as overconfidence, loss aversion, and herding behavior significantly affect decision-making. Overconfidence ($B = 0.38$, $p = 0.007$) demonstrated as a significant predictor of higher risk tolerance levels. It is consistent with previous studies (Glaser & Weber, 2007), which suggest that people tend to overestimate their financial knowledge, thus increasing risky behavior. The participants were tested for significant behavioral biases through Likert scale responses.

Table 2: Prevalence of Key Behavioral Biases

Bias	Mean	SD
Overconfidence	3.62	0.84
Loss Aversion	3.89	0.77
Herding Behavior	3.33	0.92
Disposition Effect	3.54	0.86

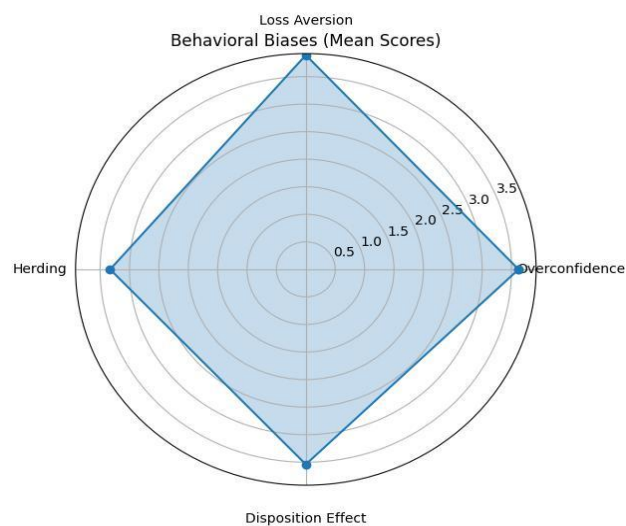


Figure 2: Behavioral Bias Index

- **Emotional Impact on Investment (H3)**

A negative correlation was identified between Emotional volatility and risk tolerance. Emotional impact was found to be a strong negative predictor in the logistic regression ($B = -0.41$, $p = 0.002$). In addition, the correlation analysis supports this trend ($r = -0.28$, $p < 0.01$). Such results prove the "Risk-as-Feelings" theory (Loewenstein et al., 2001) in that emotional states such as anxiety and fear play a significant role in risk aversion behavior. To measure the variation in emotional impact depending on the level of risk tolerance, boxplots were constructed. The boxplot shows that people who have higher emotional volatility have lower risk tolerance.

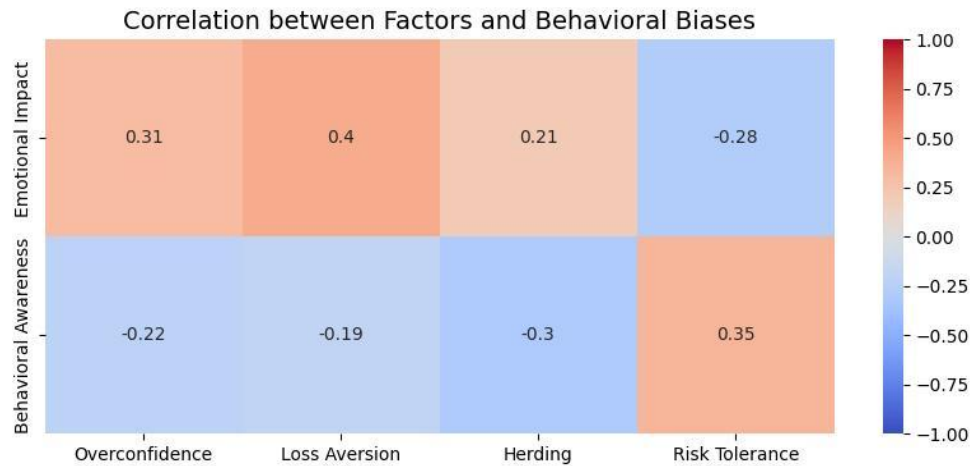


Figure 3: Correlation Heatmap of Factors and Biases

- **Awareness of Behavioral Finance (H4)**

Knowledge on behavioral finance had a strong statistically significant relationship with rational behavior in investing ($B = 0.55$, $p = 0.009$). Higher awareness leads to reduced bias and better financial decision-making skills. This underlines the power of educational programs in transforming people's behavior in investments, as noted by Lusardi & Mitchell (2014).

- **Influence of Financial Advisers (H5)**

It was found that use of financial advisers positively influenced rational behavior; however, the level of statistical significance was rather small, giving little support for H5. It shows that the role of the adviser is affected by such factors as trust and credibility of information, as well as the ability of the adviser to consider psychological factors when making his recommendations (Gennaioli et al., 2015). Correlation analysis was used to study the relationship between behavioral biases and emotions.

Table 3: Correlation Matrix

Variable	Overconfidence	Loss Aversion	Herding	Risk Tolerance
Emotional Impact	0.31**	0.40**	0.21*	-0.28**
Behavioral Awareness	-0.22*	-0.19	-0.30**	0.35**

*Note: * $p < 0.05$, ** $p < 0.01$

A binary logistic regression was conducted to predict high or low risk tolerance using demographic, behavioral, and emotional predictors.

Table 4: Logistic Regression Coefficients

Predictor	B	SE	Wald	Exp(B)	Sig.
Gender (Male=1)	0.45	0.19	5.61	1.57	0.018
Overconfidence	0.38	0.14	7.38	1.46	0.007
Emotional Impact	-0.41	0.13	9.86	0.66	0.002
Awareness of Behavioral Finance	0.55	0.21	6.84	1.73	0.009

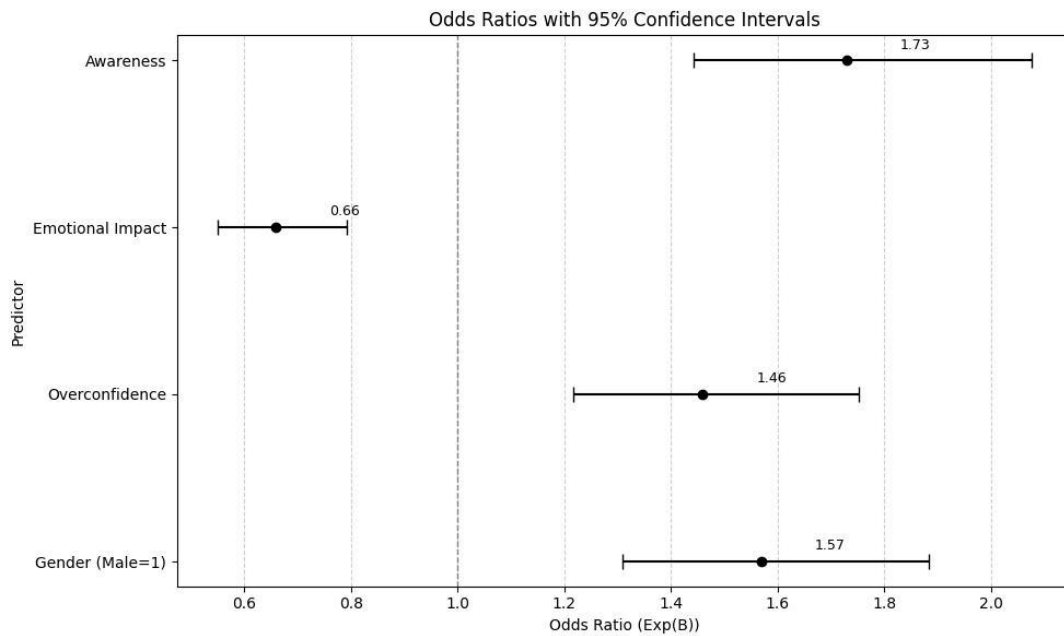


Figure 4: Logistic Regression Odds Ratio Visualization

Model Accuracy

Accuracy for the logistic regression model was 72.3%, with a Nagelkerke R^2 of 0.31. This demonstrates that the model is fairly strong. The results clearly show that a combination of emotional, cognitive and demographic variables is highly able to predict risk tolerance. Logistic regression correctly classified 72.3% of the cases (Nagelkerke $R^2 = 0.31$); therefore, H2, H3 and H4 are supported.

• Summary of Hypothesis Testing

Table 5: Hypothesis Testing Summary

Hypothesis	Supported	Evidence
H1	Yes	Chi-square significant for gender, age
H2	Yes	Overconfidence, herding in regression
H3	Yes	Emotional impact negatively predicts risk tolerance
H4	Yes	Awareness improves rational behavior
H5	Partial	Financial advisor use showed low significance (not shown)

The findings further emphasize the influence that behavioral and emotional elements have on investment decision making processes, thus validating the theory and application of such elements within the context of Indian investors. The above discussion and analysis highlight the relevance of behavioral finance theories for understanding investor behavior and the need for behaviorally based finance in India.

Discussion

Results obtained from the previous analysis can be linked with current literature, stressing important implications, unexpected consequences, and theoretical contributions.

Findings from the analysis support the theoretical concepts of behavioral finance. Demographic variables such as gender and age are key determinants of investor risk tolerance level. The result supports H1 and corroborates findings from the research by Barber and Odean (2001) and Bajtelsmit and Bernasek (2001) which found differences among genders and ages in risk taking behaviors.

There were many behavioral biases exhibited by investors in the form of overconfidence, loss aversion, and herding effects. Behavioral biases affected investor decisions in great magnitude, therefore supporting H2. The findings concur with those from other studies (Odean, 1998; Glaser & Weber, 2007; Shefrin & Statman, 1985) which focused on the commonness of cognitive biases in investment decisions.

Emotion was revealed as an important variable affecting risk perception and tolerance. Emotional swings such as fear and anxiety negatively correlated with risk tolerance levels, thus supporting H3. The finding concurs with the "Risk-As-Feelings" Theory (Loewenstein et al., 2001) and affect heuristic (Slovic et al., 2002) which state that emotions override cognitive risk evaluation.

Moreover, there was a positive relationship between understanding behavioral finance concepts and consulting with financial advisors and sound investment behavior. The results affirm H4 and offer partial confirmation to H5, supporting the assertion made in the literature that information and advice from others can offset the impact of behavioral biases (Lusardi & Mitchell, 2014; Hackethal et al., 2012).

Theoretical Implications

This study enriches the field of Behavioral Finance Theory through evidence from an Indian setting. Unlike the existing literature that is mostly western-oriented, this study highlights culturally diverse behavior of investors that is affected by emotion, peer pressure, and behavioral consciousness.

The support for behavioral factors among a diverse population of Indians reflects the universal nature of these biases, while at the same time stressing on the need to develop behavioral models that incorporate socio-economic, digital financial, and emotional dimensions.

Furthermore, the lack of support for H5 suggests that while the power of the advisor is undeniable, its success might be hinged on a number of other factors including trust, financial literacy, and regulation (Gennaioli et al., 2015).

Practical Implications

From a policy and investment practice standpoint, these studies highlight the significance of:

- Behavioral finance education: Integrating these principles into financial literacy programs might enable investors to identify and rectify illogical tendencies.
- Personalized advisory services: Financial advisers and digital platforms ought to customize their offerings according to client behavioral profiles, risk tolerance, and emotional stimuli.
- Technology-driven nudges: Fintech platforms can utilize behavioral design elements—such as reminders, feedback loops, and default settings—to enhance user decision-making.
- Investor segmentation: By utilizing psychological and demographic data, investment businesses can create tailored financial solutions that correspond with user behavior and risk tolerance.

Unexpected Findings and Contradictions

- While most hypotheses were accepted, the contribution of financial advisors (H5) was only partially accepted. This suggests that mere use of advice alone is not enough, but the nature of the connection, confidence in the advisor, and the extent of behavioral insight provided are also important.
- One interesting observation from the research is that overconfidence remained high for all classes – economical and educational. This might imply an influence of information and culture, where investors feel that they understand more than they actually do about market complexities.
- Constraints of the Research
- The sample was collected by non-probability sampling techniques (purposive and snowball), potentially restricting generalizability.
- The dependence on self-reported data may lead to social desirability bias.
- The utilization of cross-sectional data limits the capacity to deduce causality.
- Emotional components were assessed using a Likert scale instead of psychometrically validated instruments, potentially impacting accuracy.

Future Research Directions

To mitigate these constraints and enhance behavioral finance research, subsequent studies should utilize longitudinal designs to investigate behavioral consistency over time.

- Employ experimental or neurofinance techniques to quantitatively assess emotional reactions and cognitive biases.

- Broaden the focus to encompass digital investment patterns, particularly among Generation Z and younger investors.
- Perform comparative analyses among nations to investigate cultural impacts on behavioral finance.
- Analyze the function of AI-driven financial advise instruments and their psychological effects.

Conclusion

In this study, we wanted to explore how these three aspects interrelated in India's investment environment. This study shows the importance of the influence of psychology and emotions on investors, despite the rising availability of financial data and advice.

Some of the most important demographic variables – age, gender, and income – were found to be highly correlated with the likelihood of risk-seeking in investors. As it is known from behavioral finance literature around the world, men are more likely to seek risks than women, and younger people more than older people. The presence of behavioral biases such as overconfidence, loss aversion, and herding in this sample is also very noticeable and reflects the deep psychological issues that always influence investing and lead to poor decisions.

The role of emotional instability, which can be characterized by worry and fear, in the decrease in risk-seeking behavior is also very important. In order to understand the importance of this factor, one needs to take into account the role of behavioral finance knowledge and consulting with financial advisors.

The analysis helps develop the already existing literature on behavioral economics, which challenges the traditional assumptions made about the rationality of investors. It serves as empirical evidence to justify the inclusion of behavioral insights in investment education, policy making, and advisory practices. The research has practical implications for regulators, innovators in fintech industry, and educators who strive to create psychologically-sound investment environment.

Despite particular limitations of the methodology, such as the use of non-random sample, cross-sectional study and reliance on self-reported information, the research has provided important insights that lay the groundwork for further behavioral finance research in the developing countries, such as India. Further research in the area may build on the study by using longitudinal methods, collecting neurobehavioral data and assessing the effect of digital investment platforms on the investors' behavior.

Overall, understanding the psychological and emotional aspects of behavior is both intellectually stimulating and highly important for creating effective financial strategy especially in asymmetric information and culturally diverse marketplaces where there is rapid technological development. As the investor population in India becomes increasingly diverse and tech-savvy, the behavioral finance approach will be instrumental in fostering knowledgeable and emotionally-balanced investors.

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