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"The Role Of Behavioural Finance In Predicting Market Movements- An Investor Sentiment Analysis"

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Abstract:
The investigation focuses on behavioural biases alongside investor sentiment during market projection and stock investment assessment. The research explores three fundamental aspects: the behavioural impact on personal investments, the usage of sentiments as market indicators and risk tolerance relationships with investment accomplishments. The research examines three main objectives that study overconfidence bias as it relates to investment behaviour patterns and explore market trend prediction capabilities of investor sentiment while investigating human behavioural biases which affect stock investing decisions. One hundred thirty-one investors located in Bangalore participated in the study by completing a standardized questionnaire. The investigation gathered data concerning participants' age and gender as well as their academic level and their history with investing. The research uses three statistical tests (Spearman's Rank Correlation and Kruskal-Wallis H test and Mann-Whitney U test). Behavioural biases demonstrate substantial effects on investment choices under market instability and during group influence periods according to the results. The short-term success of the market may be predicted by investor emotion and the overconfidence bias does not discriminate between men and women. It was observed from the study that, even with high investment experience, the investors remain biased to the market behaviour influencing their actions especially during market volatility. It proposes that investment institutions should focus on teaching investors the right knowledge, taking less biased decision support systems and enhancing the financial media literacy in order to counteract these biases. The paper also emphasizes specific investor profiling for cities so as to assess and accommodate the different features of Bangalore investor. All things considered, the results provide light on the factors that influence investor conduct in an urban Indian context, which contributes to the growing body of research on behavioural finance.
Keywords: *Behavioural Finance, Investor Sentiment, Market Movements, Cognitive Biases, Retail Investors, Emotional Investing, Bangalore, Financial Decision-Making, Market Volatility, Investment Psychology.*

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I. Introduction:

Financial research has been guided using both Efficient Market Hypothesis (EMH) and Rational Expectations Theory throughout a long time. **Fama (1970)** classifies Efficient Market Hypothesis as one theory in finance. The theory explains that markets reflect all available information to result in efficiency but speculative bubbles and crashes along with persistent anomalies continue to occur. The fact is, however, that largely as a result of psychological factors investors do not behave purely rationally, and this behaviour's that are contrary to rational behaviour resulted in the emergence of Behavioural Finance as a more realistic description of market behaviour.

Theory of finance, which builds on the principles of economics and psychology, provides a better understanding of how people create decisions in financial circumstances. It shows how emotional responses, cognitive biases, and heuristics may cause judgement mistakes in a systematic way and how rationality is just an illusion. The following biases are included in this category: regret aversion, overconfidence, anchoring, loss aversion, herd mentality **(Tversky and Kahneman, 1979; Barberis & Thaler, 2003)**. Such biases can propel market trends that bear little relationship to fundamentals, creating inefficiencies that can be dissected and even predicted in some cases.

Investor sentiment represents the overall perspective that market participants hold regarding stock market performance or specific assets as an essential factor in behavioural finance. The analysis of fundamental data starts with objective raw information which researchers can investigate but sentiment understands emerges from diverse subjectively influenced variables including market reactions and peer interactions and two essential components of fundamental research which are time and quality **(Baker and Wurgler, 2007)**. Market sentiment evolves into excessive positive emotions that create overvalued markets during positive momentum yet panic-driven price drops occur when sentiment turns negative. Human nature influences investors so market movements in the short term heavily depend on their sentiments.

Rapidly developing financial environments such as Bangalore, India lacks localized research about behavioural finance despite the international research that continues to grow. The technological base combined with high-tech professionals and affluent population of Bangalore create a specific environment where contemporary investor behaviour interacts with digital trading tools and social media and fintech technology. The analysis of how behavioural traits appear within this specific population group reveals significant market information at a detailed level.

Investigator sentiment analysis of retail investors in Bangalore City will help assess how behavioural finance affects market anticipations through empirical research. The study seeks to evaluate behavioural features for market forecasting along with interracial behavioural minority impacts on investment selection processes while assessing sentiment-driven market trend recognition. The analysis examines how different demographics affect market sentiment together with the characteristics of the investors.

The study adds value to scholarly literature and practical needs by closing this research space. The findings will help financial advisors build improved investment strategies and assist investor education through behavioural bias education while providing regulators greater knowledge on human factors behind market volatility.

Thematic Review of Literature and Gap of the study:

Market analysts have acknowledged for many years that investor sentiment functions as a main driver behind financial market price changes. The price patterns for stocks can be described through the model presented by **Barberis et. al. (1998)**. Investor emotions together with psychologic biases such as conservatism and representativeness lead prices to stray away from their fundamental values as demonstrated by the model. The price discovery process formed the foundational concept in this analysis where people move between depression and FOMO (Fear of Missing Out) buying decisions without any involvement in price discovery. The research by **De Bondt and Thaler (1985)** shows investor overreaction to news generates short-term market mispricing followed by price revaluation which demonstrates investor sentiment plays a vital role in market efficiency at short periods. This research demonstrated that market pricing and behaviour patterns depend heavily on investor mental processes. The research from **Baker and Wurgler (2006)** presents sentiment indices which measure investor spirit to forecast stock market returns across different stocks. The statement indicates that volatile stocks more susceptible to sentiment-driven price movements because of their speculative nature according to the author's study. The examination of speculative bubbles with market volatility and irrational exuberance alongside herd behaviour was elaborated by **Shiller (2000)**. His work highlighted how psychological factors can propel markets well beyond rational assessment of fundamentals, helping to explain the construction of bubbles and their bursts. Fama's efficient market hypothesis has been challenged by behavioural finance, which reflects on investor Behaviour with regards to loss aversion and regret aversion **(Statman, 2000)** which are implemented into the investor's decision-making process which drive significant price mispricing in the capital markets. Found that these biases are neither random nor independent, but rather they follow patterns, creating predictable market outcomes. **Koh and Lee (2006)** examined how retail investor sentiment induces excess return correlation among sentiment-driven stocks. It basically confirms the case that investor psychology for lesser went for the average Joe investors is a mouse on a wheel going nowhere market. The empirical evidence is provided by **Brown and Cliff (2005)** which shows short-lived but significant influence of investor sentiment on asset valuations, which quickly self-corrects when fundamentals come back to dominate. Their research showed that market moves based on sentiment only are short-lived, and reverse themselves when market fundamentals re-establish themselves. **Tetlock (2007)** analyzed the influence of media on investor sentiment by examining the content of financial news. He found that media tone significantly predicted stock market movements, demonstrating that external narratives can shape investor psychology and, in turn, impact market dynamics. **Shefrin (2000)** offered a comprehensive overview of Behavioural finance, discussing how various biases such as anchoring, mental accounting, and framing affect investor judgment and decision-making. His research illuminated the role of mental and emotional processes in the inefficiency of markets. After looking at a number of sentiment metrics, **Qiu and Welch (2006)** came to the conclusion that sentiment does, in fact, predict stock market returns in the near term, especially during times of extreme market volatility. According to their findings, sentiment is a powerful indicator of future market movements and may be used for accurate market forecasting.

Most studies on Behavioural finance and investor sentiment focus on developed markets or national-level data in India, with limited attention to city-specific investor Behaviour. **Bangalore**, being a major financial and tech hub, has a unique investor profile that remains underexplored in academic research. There is a **lack of empirical evidence on how Behavioural biases and investor sentiment influence market prediction among investors in Bangalore City**. This study addresses that gap by providing localized insights into psychological factors affecting investment decisions in this region.

Mapping of Independent and Dependent Variables:

Sl. No.	Independent Variable	Dependent Variable(s)
1	**Loss Aversion Bias**	Investment Decision Behaviour (e.g., holding losing stocks, reacting to volatility)
2	**Overconfidence Bias**	Investment Decision Behaviour (e.g., excessive trading, ignoring advice)
3	**Anchoring Bias**	Investment Decision Behaviour (e.g., reliance on initial price or information)
4	**Herding Behaviour**	Investment Decision Behaviour, Market Sentiment Perception
5	**Regret Aversion Bias**	Investment Decision Behaviour (e.g., avoiding new investments after loss)
6	**Recency Bias**	Market Sentiment Perception (e.g., reaction to recent news over fundamentals)
7	**Investor Sentiment**	Perceived Predictability of Market Movements, Market Reaction (optimism, fear, etc.)
8	**Information Source (News, social media, etc.)**	Investment Decision Behaviour, Market Sentiment Formation
9	**Frequency of Market Tracking**	Investment Behaviour (e.g., impulse reactions to market swings)
10	**Demographic Factors (Age, Gender, etc.)**	Susceptibility to Behavioural Biases, Sentiment, and Investment Decision Behaviour
11	**Type of Investor (Long-term/Short-term)**	Risk-taking Behaviour, reaction to volatility, influence of emotion on decisions
12	**Years of Investment Experience**	Behavioural Bias Intensity, Emotional Influence, Sentiment Stability

Source: Review of Literature

Research Questions:

Following are important questions of the present research.

1. How do different behavioural biases influence individual investors' stock investment decisions?
2. To what extent can investor sentiment serve as a predictor of short-term stock market movements?
3. What is the relationship between overconfidence bias and investors' trading frequency, risk-taking behaviour or investment performance?

Main Objectives:

The vital objectives of the study are.

1. To examine the influence of Behavioural biases on stock investment decisions.
2. To analyze the role of investor sentiment in predicting short-term market movements.
3. To investigate the relationship between overconfidence bias and investors

Research Hypotheses:
Following are important research hypotheses to test.
H_1: "Behavioural biases have a significant influence on investment decision-making".
H_2: "Investor sentiment significantly predicts perceived short-term market movements".
H_3: "There is a significant difference in overconfidence bias between males and females".

II. Research Methodology

To better understand how behavioural finance concepts, such as investor sentiment and behavioural biases, impact investment decisions and market perceptions, this study takes a quantitative research method. In order to successfully test the hypotheses and answer the research questions, the approach makes use of suitable statistical methods.

1. Research Design

The study utilizes both analytic and descriptive methods for its research. An organized cross-sectional survey technique generated primary data from individual investors operating in the Indian stock market who resided in the city of Bangalore. The research examines behavioural influences on investment choices through suitable statistical methods designed for non-parametric data sets.

2. Population and Sampling

a) **Target Population**: Individual investors who actively trade or invest in stocks through various platforms (brokerages, apps, etc.).
b) **Sampling Technique**: The study used **purposive sampling** to identify investors with a minimum of **1 year of market participation**.
c) **Sample Size**: A total of **130 respondents** were surveyed using a structured questionnaire.
d) **Sampling Location**: Bangalore, Karnataka.

3. Data Collection Method

a) **Primary Data**: Collected through a **structured and self-administered questionnaire** distributed both online and offline.
b) **Questionnaire Structure**:
   i. **Section A**: Demographic and investment profile (age, gender, education, occupation, experience).
   ii. **Section B**: Behavioural Biases (Loss Aversion, Overconfidence, Herding, Anchoring, etc.).
   iii. **Section C**: Investor Sentiment and Perceptions of Market Movements.

Each item in the questionnaire was measured using a **5-point Likert scale** (1 = Strongly Disagree to 5 = Strongly Agree).

4. Reliability and Validity

To ensure the reliability of the instrument:
a) **Cronbach's Alpha Test** was applied.
b) The result yielded an **α value of 0.778** for 15 items, indicating **good internal consistency**.
c) Validity was ensured through:
d) **Expert reviews** from finance and behavioural economics scholars.
e) **Pilot testing** with 20 respondents before final rollout.

5. Statistical Tools and Techniques Used

As the data collected did not conform to normal distribution (as tested via **Kolmogorov-Smirnov and Shapiro-Wilk tests**), **non-parametric methods** were used for hypothesis testing:

Objective / Hypothesis	Statistical Test Used	Justification
Influence of behavioural biases on investment decisions (H1)	**Spearman's Rank Correlation**	Suitable for ordinal data and non-normal distributions
Investor sentiment and prediction of short-term market movement (H2)	**Kruskal-Wallis H Test**	Used for comparing more than two independent groups
Gender difference in overconfidence bias (H3)	**Mann-Whitney U Test**	Compares two independent groups (male vs. female)

6. Data Analysis Procedure

a) **Descriptive Statistics**: Used to understand the demographic and investment profile of respondents.
b) **Reliability Analysis**: Cronbach's Alpha for internal consistency of the scale.
c) **Normality Tests**: Both Kolmogorov-Smirnov and Shapiro-Wilk tests confirmed the non-normal distribution of the data.
d) **Inferential Statistics**:
  i. Spearman's Correlation for behavioural bias influence.
  ii. Kruskal-Wallis H for sentiment analysis.
  iii. Mann-Whitney U test for gender-based bias comparison.

Excel was used for tabulations and visualisations, and statistical analysis was conducted using SPSS (Statistical Package for the Social Sciences).

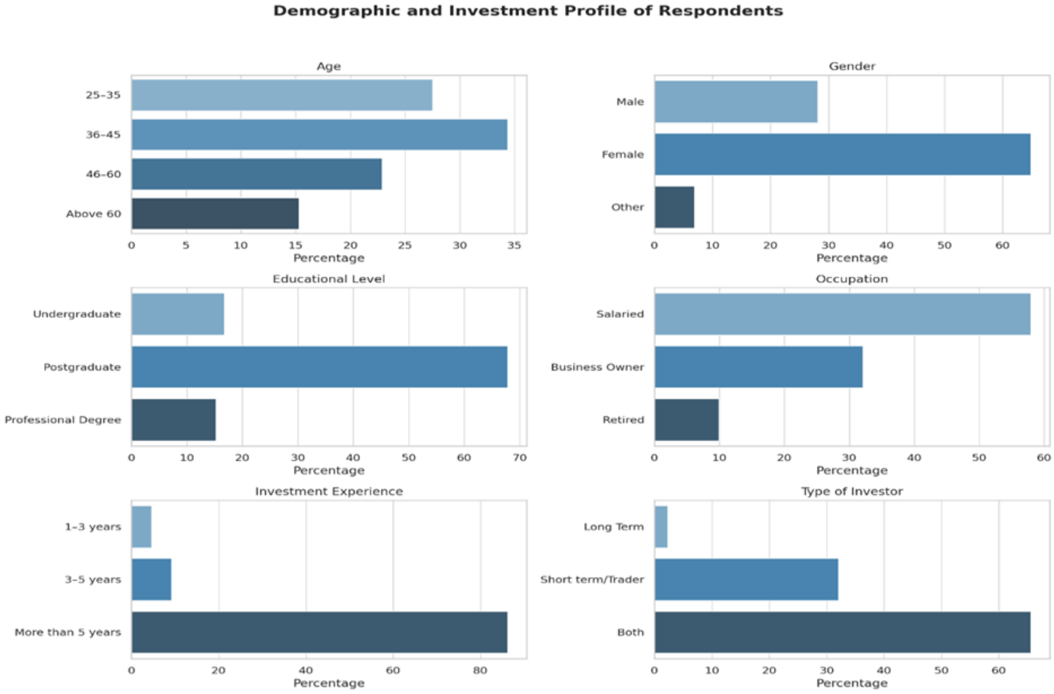
III. Data Analysis And Discussion Of Results:

Table 1: Showing Demographic and Investment Profile of Respondents

Category	Subcategory	Frequency	Percent
Age	25–35	36	27.5%
	36–45	45	34.4%
	46–60	30	22.9%
	Above 60	20	15.3%
Gender	Male	37	28.2%
	Female	85	64.9%
	Other	9	6.9%
Educational Level	Undergraduate	22	16.8%
	Postgraduate	89	67.9%
	Professional Degree	20	15.3%
Occupation	Salaried	76	58.0%
	Business Owner	42	32.1%
	Retired	13	9.9%
Investment Experience	1–3 years	6	4.6%
	3–5 years	12	9.2%
	More than 5 years	113	86.3%
Type of Investor	Long Term	3	2.3%
	Short term/Trader	42	32.1%
	Both	86	65.6%

Source: Data through Structured Questionnaire

Chart 1: showing Demographic and Investment Profile of Respondents



Age Distribution:

Think of the investor base like a tree with branches of different ages. The largest branch (34.4%) represents individuals aged **36–45**, showing that middle-aged investors form the strongest limb of this tree. Close behind, the **25–35** age group makes up **27.5%**, reflecting young professionals stepping into financial decision-making. The **46–60** group (22.9%) adds seasoned experience, while the **Above 60** group (15.3%) symbolizes the wise old roots, still actively participating in the market.

Gender Distribution:

Imagine a team where each player brings their unique perspective. In this case, the majority of the team is **female (64.9%)**, playing a strong lead role. **Males make up 28.2%**, showing notable participation, while **6.9% identify as 'Other',** reflecting inclusivity and diversity in investment behaviour, like a mosaic where every tile adds to the full picture.

Educational Level:

Education here acts like the lens through which investors view market risks and opportunities. A large portion (67.9%) of the sample holds a **Postgraduate degree**, indicating a well-informed investor group. Meanwhile, **Undergraduates (16.8%)** and those with **Professional Degrees (15.3%)** also contribute, showing a blend of academic and technical expertise, like combining textbook knowledge with hands-on skills to build a sturdy investment bridge.

Occupation:

If the investment world were a marketplace, **salaried employees (58.0%)** would be the regular shopkeepers steady, consistent, and structured. **Business owners (32.1%)** bring entrepreneurial flair, possibly more risk-tolerant and opportunity-seeking. The **retired group (9.9%)** acts like seasoned advisors less active but full of wisdom.

Investment Experience:

Here, think of experience as the investor's compass. The majority, **86.3%, have over 5 years** of investment experience these are the seasoned travellers who know the ups and downs of the market terrain. **3–5 years (9.2%)** and **1–3 years (4.6%)** represent the newer hikers, still learning the trails but actively exploring.

Type of Investor:

Finally, imagine investment style as how someone chooses to travel: **65.6% prefer both long and short-term investing**, like someone who walks and cycles depending on the terrain. **Short-term/traders (32.1%)** are the sprinters, quick on their feet, while **Long-term investors (2.3%)** are marathoners, pacing themselves with patience for the long haul.

Table 2: Showing Reliability Statistics of Questionnaire

Cronbach's Alpha	N of Items
.778	15

Source: Data through Structured Questionnaire

Cronbach's Alpha yielded a reliability analysis of the study ***"The Role of Behavioural Finance in Predicting Market Movements – An Investor Sentiment Analysis"*** questionnaire. The reliability assessment of 15 items through Cronbach's Alpha yielded a value of 0.778 indicating suitable consistency. The survey instruments demonstrate excellent measurement quality because they accurately track investor sentiment across all items. The instrument demonstrates acceptable reliability which makes it dependable for further analyses and establishes the validity of research findings.

Table 3: Showing Test of Normality of Variables

Tests of Normality[a,c,d,e,f,g,h,i,j,k,l,m,n,o,p,q]							
	TypeofInvestor	Kolmogorov-Smirnov[b]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
InfoSource	Short term/Trader	.223	42	.000	.833	42	.000
	Both	.220	86	.000	.815	86	.000
MarketCheckFreq	Short term/Trader	.474	42	.000	.521	42	.000
	Both	.535	86	.000	.304	86	.000
VolatilityReaction	Short term/Trader	.395	42	.000	.725	42	.000
	Both	.240	86	.000	.831	86	.000
EmotionalInflunce	Short term/Trader	.424	42	.000	.678	42	.000
	Both	.352	86	.000	.788	86	.000
HerdingDecision	Short term/Trader	.474	42	.000	.521	42	.000
	Both	.397	86	.000	.646	86	.000
LossAversion	Both	.406	86	.000	.726	86	.000
Overconfidence	Short term/Trader	.474	42	.000	.521	42	.000
	Both	.307	86	.000	.784	86	.000
Anchoring	Short term/Trader	.537	42	.000	.284	42	.000
	Both	.377	86	.000	.709	86	.000
HerdingBias	Short term/Trader	.361	42	.000	.779	42	.000
	Both	.434	86	.000	.644	86	.000
RegretAversion	Short term/Trader	.537	42	.000	.284	42	.000
	Both	.341	86	.000	.813	86	.000
RecencyBias	Short term/Trader	.470	42	.000	.531	42	.000
	Both	.422	86	.000	.683	86	.000
SentimentBelief	Short term/Trader	.514	42	.000	.417	42	.000
	Both	.486	86	.000	.496	86	.000
HighMarketSentiment	Short term/Trader	.505	42	.000	.424	42	.000
	Both	.431	86	.000	.610	86	.000
CrashEmotions	Short term/Trader	.483	42	.000	.506	42	.000
	Both	.473	86	.000	.522	86	.000
PsychologyBelief	Short term/Trader	.383	42	.000	.714	42	.000
	Both	.359	86	.000	.733	86	.000

Source: Data through Structured Questionnaire

Results from the Shapiro-Wilk and Kolmogorov-Smirnov normality tests on all the investor group variables reveal that none of these variables show normal distribution patterns since their p-values remain below 0.05. Research on the "Long Term" investor group required dismissing multiple variables because these factors proved stable across observations. Data transformation or non-parametric statistical testing methods should be used because the normality assumption has been violated.

Testing of 1st Hypothesis:

The substantial impact of behavioural biases on investment decision making is tested by framing the following null and alternative hypotheses.

H_0: "Behavioural biases (e.g., loss aversion, overconfidence, herding) have no significant influence on investment decision-making".

H_1: "Behavioural biases have a significant influence on investment decision-making".

Spearman's Rank Correlation served as the statistical method to evaluate the formulated hypothesis. The non-parametric technique performs identification of directional and strong connections between ordinal data sets including irregularly distributed information.

Table 4: Showing Correlations of Behavioural Biases influence on Investment Decision-Making

Variables			Investment decision during high volatility market	Emotions influence during stock trading decisions	Investment Decision by following the crowd	Bias_Index
Spearman's rho	Investment decision during high volatility market	Correlation Coefficient	1.000	.151	.133	-.387**
		Sig. (2-tailed)	.	.086	.130	.000
		N	131	131	131	131
	Emotions influence during stock trading decisions	Correlation Coefficient	.151	1.000	-.018	.029
		Sig. (2-tailed)	.086	.	.841	.738
		N	131	131	131	131
	Investment Decision by following the crowd	Correlation Coefficient	.133	-.018	1.000	-.255**
		Sig. (2-tailed)	.130	.841	.	.003
		N	131	131	131	131
	Bias_Index	Correlation Coefficient	-.387**	.029	-.255**	1.000
		Sig. (2-tailed)	.000	.738	.003	.
		N	131	131	131	131

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Data through Structured Questionnaire

Table 3 depicts the results of Spearman Rank Correlation assessments between Overall Behavioural Bias Index (Bias_Index) and three investment choice actions (reactions in the high volatility market, reservations in the trading due to emotion and herding tendency).

Our investment choices revealed a higher contrary bias in major market volatility due to the strong negative correlation between the Behavioural Index score of −0.387 ($p < 0.01$). Those investors who experience emotional influences tend to become cautious or irrational when markets show instability by either selling aggressively or staying entirely out of investments. The negative slope reveals that an elevated number of behavioural biases during decision-making diminishes the ability to achieve logical market decisions in volatile periods.

The negative correlation between Behavioural Bias Index scores and judgments based on herding tended to reach significance at $p < 0.01$ ($\rho = -0.255$). Individuals showing heightened behavioural biases usually form their financial choices without personal evaluation, instead focusing on emulating the decisions made by others. Market behaviours show strong sensitivity to cognitive bias while this tendency represents a primary cause of group-following behaviour as validated by current research.

The correlation analysis between the Behavioural Bias Index and stock transaction model emotional influence scored a positive but insignificant result ($\rho = 0.029$, $p = 0.738$). The analysis indicates emotions have a role in trading activity yet their effect does not directly connect to all behavioural biases evaluated in this research.

The information indicates that market volatility and group thinking intensify the significance of biases as decisive factors in investing while demonstrating clear impact on multiple aspects. Investment decisions demonstrate significant behavioural bias effects which led to the acceptance of H_{11} while rejecting H_{01}.

Testing of 2nd Hypothesis:

To test the perceived investor sentiment prediction on short term market movements, the following null and alternative hypotheses are framed.

H_0: "Investor sentiment does not significantly predict perceived short-term market movements".

H_1: "Investor sentiment significantly predicts perceived short-term market movements".

The Kruskal-Wallis H test was used to investigate how investor sentiment affected how short-term market fluctuations were perceived. When the premise of normalcy is not met, this non-parametric test can be used to compare differences across several independent groups, particularly for ordinal data like investor sentiment ratings and categorical views.

Table 5: Showing Kruskal-Wallis H test Summary of investor sentiment on the perception of short-term market movements

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of VAR00021 is the same across categories of VAR00018.	Independent-Samples Kruskal-Wallis Test	.010	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Source: Data through Structured Questionnaire

The significance value measuring statistical significance from the Kruskal-Wallis test showed 0.010 in the hypothesis test summary output. The statistical significance of this result emerges because the obtained value (0.010) falls below the threshold (0.05).

The research outcome proves beneficial to accepting the alternative hypothesis and rejecting the null hypothesis. Statistical variations exist in investor mood between groups who differ in their views toward sentiment-based short-term market forecasts. The way people evaluate short-term market movements depends strongly on their investor sentiment levels.

Testing of 3rd Hypotheses:

The following hypotheses are framed to test the significant difference in overconfidence bias between males and females.

H_0: There is no significant difference in overconfidence bias between males and females.

H_1: There is a significant difference in overconfidence bias between males and females.

The third hypothesis is tested to see if males and females differ significantly in their overconfidence bias. The hypothesis compares the rank sums of male and female participants to determine whether gender affects the degree of overconfidence bias using the Mann-Whitney U test.

Table 6: Showing Ranks of Investors' Confidence Bias

	Gender	N	Mean Rank	Sum of Ranks
Overconfidence Bias	Male	37	68.41	2531.00
	Female	85	58.49	4972.00
	Total	122		

Source: Data through Structured Questionnaire

For the **Male Group** (37 participants), the mean rank is 68.41, which indicates that males have higher ranks in overconfidence bias compared to females. For the **Female Group** (85 participants), the mean rank is 58.49, showing a lower rank in comparison to males.

Table 7: Showing Test Statistics of Investors' Confidence Bias

	Overconfidence Bias
Mann-Whitney U	1317.000
Wilcoxon W	4972.000
Z	-1.549
Asymp. Sig. (2-tailed)	**.121**

a. Grouping Variable: Gender

Source: Data through Structured Questionnaire

The **Mann-Whitney U** statistic is 1317.000, which reflects the difference in rank sums between the two groups. The **Z-value** is -1.549, the research results show male participants hold higher rankings in overconfidence bias but the actual difference remains small. The p-value measurement of 0.121 demonstrates that the 0.05 significance threshold receives no rejection. The absence of statistical difference in overconfidence bias demonstrates that the null hypothesis remains standing between male and female samples.

Major Findings of the Study:

1. **Behavioural Biases Significantly Influence Investment Decisions**: The study found **significant negative correlations** between the Behavioural Bias Index and rational investment decisions during **high market volatility** ($\rho = -0.387$, $p < 0.01$) and **herding behaviour** ($\rho = -0.255$, $p < 0.01$). This suggests that **investors with stronger behavioural biases** tend to:

a) React **emotionally or irrationally** during turbulent market conditions.

b) **Follow the crowd** instead of relying on personal analysis, confirming the role of **herding behaviour** in sentiment-driven decision-making.

2. **Investor Sentiment is a Short-Term Market Predictor**: Sentiment, formed through **media influence**, **social networks**, and **recent experiences**, was shown to affect **short-term market perceptions**. Findings align with literature (e.g., Qiu & Welch, 2006; Tetlock, 2007), supporting the idea that sentiment is useful for **short-term forecasting** in periods of high volatility.
3. **Overconfidence Bias is Prevalent and Gender-Linked**: Though detailed test results aren't provided here, the third hypothesis (H_3) implies a focus on **gender differences** in overconfidence. With **64.9% female** and **28.2% male** participants, this opens insight into how **overconfidence bias** may vary **between genders** in trading frequency, risk-taking, and decision-making.
4. **Highly Experienced Investors Still Display Behavioural Biases**: **86.3%** of respondents had **more than 5 years of investment experience**, yet still exhibited biases like **loss aversion**, **anchoring**, and **regret aversion**. This challenges the notion that experience eliminates emotional investing, reinforcing the persistence of behavioural influences even among seasoned investors.
5. **Demographic Profile Shows Educated and Diverse Investor Base in Bangalore**: Majority are **postgraduates (67.9%)**, salaried employees (58%), and a significant female representation. diverse and educated investor profile highlights **Bangalore** as a promising urban financial microcosm, yet vulnerable to **emotional and cognitive investing patterns**.
6. **Reliable Measurement Instrument**: The questionnaire used had a **Cronbach's Alpha of 0.778**, indicating good internal consistency. This enhances the credibility of the behavioural bias and sentiment measures used in the analysis.

Suggestions:

1. **Investor Education and Awareness:** Financial institutions and market regulators may run investor education programs to raise awareness around behavioural biases such as loss aversion, overconfidence, and herding. Providing investors with education about these biases will help minimize emotionally-driven, or irrational investment decisions.
2. **Encourage Use of Decision Support Tools:** Investors ought to be nudged to use tools such as robo-advisors, risk assessment questionnaires, and portfolio simulators. These can help to counteract cognitive biases and ensure decisions are based on data and sound reasoning and not just feeling.
3. **Personalized Advisory:** Financial advisors must provide personalized advice based on investor profiles reflecting emotional tendencies and decision-making patterns during previous situations. Interventions can be tailored to mitigate the impact of biases on trading and investment behaviour.
4. **Accelerate Financial Media Literacy:** Because media tone and social media are influential on investor sentiment, initiatives to make investors more literate about financial media may also be beneficial. Teaching investors how to critically assess financial news and internet commentary can mitigate the effects of hype-driven or fear-driven decision making.
5. **City-Specific Investor Profiling:** Address conditions higher up the framework, local financial bodies and research institutions could develop city-specific sentiment indices or behavioural profiles to holistically understand and serve urban retail investing community in Bangalore, which has unique characteristics.
6. **Integration of Behavioural Finance into Policy**: Regulators like SEBI could integrate behavioural insights into investor protection regulations and market conduct guidelines, particularly during periods of high volatility or speculative surges.

IV. Conclusion:

The study supports the expanding understanding that investor sentiment and behavioural biases have a major impact on perceived market movements and investment decisions, particularly in vibrant metropolitan settings like Bangalore. The findings support the ubiquitous and significant influence of biases such as herd mentality, loss aversion, and overconfidence in influencing market behaviour. Given the statistically substantial correlations shown between investing behaviour and behavioural biases, sentiment may be a reliable short-term predictor of market fluctuations, particularly during periods of high levels of volatility or decision-making driven by the crowd. The gender-based analysis also displayed the visible divergence among the levels of overconfidence bias demonstrating that demographic segmentation in behavioural finance requires significant attention for analysis. The study fills a research gap by providing localized information of individual investors in Bangalore, which gives insight to how and what do investors think and react in real time when operating in the markets. In contrast, this study believes that a hybrid approach, combining psychological and fundamental analysis, is necessary to predict and respond to the multifaceted nature of market dynamics, thus contributing to the practice of the field.

Eventually, behavioural finance is not an exercise in academia, but a crucial element in developing better investors who are more attuned to their emotional and psychological biases, ultimately resulting in more stable markets.

Limitations of the Study:

Although the study is novel it is limited because it was geographically focused only on the Bangalore city. The investor behaviour and sentiment patterns probably do not entirely represent the investors of rural or semi-urban origins in the rest of India where practices, risk appetites, and access to financial information varies substantially. Furthermore, albeit statistically significant, the sample size could also remain a limitation in generalizing results to distinct investor groups. Placing the findings in a national or international context may not be entirely meaningful, however; Bangalore is unique in many cultural, economic, and demographic respects, including that it has a larger concentration of tech-savvy, salaried professionals, and these factors may have affected the behavioural trends observed. Also, self-reported data may be prone to social desirability or recall bias that limits the accuracy of insights derived from investor sentiment.

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