Journal of Management Science Research Review

ISSN Online: 3006-2047
ISSN Print: 3006-2039

Volume. 5, Issue No. 1 (2026)

https://doi.org/10.5281/zenodo.20603947

Understanding Risk Tolerance and Investors' Psychology: A Behavioral Finance Approach to Decision-Making Under Market Volatility and Uncertainty

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Article History

Keywords:
behavioral finance, cognitive bias, investor psychology, overconfidence, panic selling, risk tolerance

Article History
Received on 20 Feb 2026
Accepted on 28 Feb 2026
Published on 05 March 2026

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Abstract

Background – Behavioral finance has sufficient knowledge on cognitive biases in investment decision-making but there is absence of fully integrated frameworks that incorporated the interaction between an individual risk tolerance and various psychological biases during times of market instability

Objectives – This study explored the psychological determinants of panic selling behavior among individual investors during periods of market volatility. Specifically, it examined how behavioral factors such as risk tolerance, overconfidence, and loss aversion influenced investment decisions under stress.

Methodology – Utilizing a mixed-methods research design, the study combined quantitative survey data with qualitative interviews to provide both statistical and experiential insights. The quantitative component employed structured questionnaires to measure behavioral traits and their relationship with panic selling, while the qualitative phase captured investors' narratives to explore emotional and cognitive responses to market declines.

Expected Results – Findings revealed that low risk tolerance and high loss aversion significantly predicted panic selling, while moderate overconfidence appeared to serve as a protective factor, enabling investors to remain committed to long-term strategies. Thematic analysis of interviews highlighted emotional triggers, peer influence, and cognitive distortions as recurring patterns among panic sellers. These results underscore the importance of behavioral awareness in financial decision-making and suggest that emotional regulation and behavioral coaching

ISSN Online: 3006-2047
ISSN Print: 3006-2039
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should be integrated into investor education programs.

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ISSN Print: 3006-2039

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Introduction

It comes to be understood that investor decision-making has become an intricate combination of thought, emotion, and actions which can affect financial performance, especially in times of high financial market volatility. The traditional finance theories assumed that investors were rational and made judgments using only the information that was available to them with the aim of maximizing utility (Fama, 2021). Nevertheless, this position was put under question by behavioral finance studies that proved that investors were strongly inclined to systematic biases and heuristics that tended to negatively affect their investment behavior (Barberis, 2018). These biases were particularly prominent in situations of uncertainty in the market since they were subjected to delusion due to fear and overconfidence, as well as fear of loss.

The recent increase of the global economic instability, which included the COVID-19 pandemic and geopolitical tensions, had highlighted the necessity to find the answers to how psychological aspects influenced the behavior of investors in a period of stress (Baker et al., 2020). There was some evidence indicating that higher financial market volatility elicited emotional reactions that superseded rational decision-making actions, as it induced panic selling or over-trading by the investors (Leal et al., 2021). Therefore, risk tolerance, behavioral biases, and investment decisions had become a significant field of focus among researchers as well as practitioners in assessing the relationship in place between the three concepts.

Moreover, the nature of the financial markets which was rapidly evolving with high rates of information sharing and algorithmic trading platforms had already added some levels of layers in the behavior of investors. Personal variation in risk attitudes and aversion might further increase the effects of market jolts on portfolio performance, which makes a more complex application of behavioral finance to investment education and advice even more necessary (Hoffmann et al., 2022).

1.1 Research Background

There was literature on behavioral finance which had tested different cognitive biases and their effects on risk assessment and decision strategies of investors. Loss aversion was one of the foundational theories which predicted that the outcome of a loss is more important than that of the gain under a similar amount of money, leading to behavior of overly conservative investment or liquidating prematurely during negative market effects (Kahneman & Tversky, 2013). On the other hand, overconfidence bias gave the room to the investors to overcast their knowledge and predictive skills, and this aspect commonly resulted in

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ISSN Online: 3006-2047
ISSN Print: 3006-2039

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overtrading and the underestimation of risk (Glaser & Weber, 2007). Such behavior as herding, when people adhered to the behavior of the majority, also took place in periods of high volatility in the market, enhancing price changes and systematic risk (Bikhchandani & Sharma, 2021).

This was evidenced by the findings of empirical studies which proved that risk tolerance was a stable individual level characteristic that interacts with situational variables to influence investment behavior (Grable & Lytton, 1999). High risk investors expressed increased follow-through losses in the anticipation of profit, and the low-risk investors were likely to take emotional decisions and were loss-aversive (Gao et al., 2023). It had also been identified in research that the effect of behavioral biases on portfolio choices was moderated by demographic variables, including the age, gender, and investment experience (Menkhoff et al., 2022).

Although much has been done to advance the field of behavioral finance, few studies have tried to combine quantitative risk-tolerance measures with qualitative descriptions of psychological mechanism in the face of market volatility. In addition, there had been little exploration with respect to mixed impacts of various biases, including overconfidence, loss aversion, and herding on the performance of investments during real or simulated volatility conditions. Such a discrepancy emphasized the significance of using mixed methods designs that would allow exploring the complexity of investor behavior (Zhang et al., 2022).

1.2 Research Problem

Behavioral finance had increased the knowledge on cognitive biases in investment decision-making but there was the absence of fully integrated frameworks that incorporated the interaction between an individual risk tolerance and various psychological biases during times of market instability. The said limitation complicated the creation of powerful investor education programs and commentative approaches that could reduce irrational behavior amid things like market shocks (Statman, 2019).This is the research gap which this study set out to fill by examining how risk tolerance interacts with overconfidence, loss aversion and herding tendencies to influence the outcome of the investment decisions made in simulated high-volatility environments. The fact that both quantitative surveys and qualitative interviews were used in the research allowed it to obtain more comprehensive insight into the process of suboptimal investment behavior and give some practical suggestions regarding the

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improvement of financial resilience.

1.3 Research Objectives

1. To examine the relationship between individual risk tolerance and behavioral biases (overconfidence, loss aversion, and herding) in investment decision-making during volatile market conditions.
2. To identify demographic and psychological factors that moderated these relationships.
3. To develop evidence-based recommendations for investor education and advisory practices that promote rational financial decision-making under uncertainty.

1.4 Research Questions

Q1. How did varying levels of risk tolerance influence the prevalence of behavioral biases among retail investors?

Q2. What demographic and experiential factors moderate the impact of these biases on investment decisions?

Q3. How could behavioral finance insights be integrated into advisory frameworks to mitigate irrational decision-making?

1. Literature Review

2.1 Behavioral Finance and Investor Decision-Making

Behavioral finance became one of the most important fields of knowledge that opposed the classical balance of investors as rational but considering the effects of psychology and other emotional aspects of financial decisions. The recent study noted that heuristics and mental shortcuts along with emotions considerably influenced the way investors behaved rather than being just a result of objective market information (Kumar & Goyal, 2023). Research had indicated that experienced investors were also likely to err in judgments, especially those involved in volatile markets, and it is during this occasion where uncertainty set problems and prompted hasty, usually irrational, reactions (Bhatia et al., 2022). These results supported the emerging opinion that behavioral theory was complementary to the standard financial concepts and needed to be incorporated to represent investor behavior in the real-world.

Additionally, cognitive biases were critical factors that influenced the expectations and perceptions of the investors with regards to value; some of the cognitive biases included the confirmatory bias, anchoring and mental accounting (Sahoo & Kumar, 2022). Specifically, the way the financial information was presented as either losses or gains made a serious difference as far as investment decisions were concerned (Ahmed & Riaz, 2022). Even experienced investors were found to have many behavioral patterns such as disposition effect whereby investors stuck on losing stocks but sold the winning stocks rapidly (Pandey et al., 2023).

2.2 Risk Tolerance and Individual Differences

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Risk tolerance has always been considered a primary characteristic when explaining the variance in behavior of investors. It was referred to as the desire of a person to venture into financial activities with non-determined consequences because it depended on typical personality characteristics as well as diagnosed circumstances (Dey & Debnath, 2022). Recent research indicated that demographic factors including age, gender, income level, and financial literacy variables had a large influence on the risk profile of one (Rana & Mollah, 2022). The typical case was demonstrated by younger investors and males, who were more risk-takers than older, and female investors in newly formed economies as well (Kumari & Raj, 2023).

There were also psychological dimensions. According to the study by Shaikh and Medhekar (2022) it was discovered that highly emotionally stable investors and open investors were much more likely to act on calculated risk taking, whereas neurotic investors were found to be averse to uncertainty. Notably, risk tolerance did not remain uninfluenced, it changed over time based on macroeconomic dynamics, investment experience, and exposure to market crises in the past (Roy & Banerjee, 2023). In such a way, the assessment of risk tolerance showed to be significant in the design of effective financial advisory services according to the longitudinal and contextual scales.

2.3 Cognitive Biases During Market Volatility

During market turbulence, the behavioral biases are further exaggerated, which oftentimes results in poor investment results. As an example, herding had been regarded as a common phenomenon lately during financial shocks in the world, e.g., the COVID-19 pandemic and recovery period. Prasad and Sinha (2023) state that investors were prone to simply copy the choices of other people to ensure that they do not regret or become embarrassed, irrespective of the fundamentals. Such copycat action has resulted in assets bubble creation or high sales in the market hence increasing market instability.

In the same vein, the loss aversion effect was more pronounced in volatile times where the investors overweighed on loss prevention rather than gain acquisition (Bose & Saha, 2022). It would frequently lead to the premature selling of assets or abandoning the market all together destroying long-term performance in the portfolio. Another such notion was the overconfidence bias; those investors who overestimated their predictive performance were more likely to trade more and were more prone to underestimate the risk and overestimate the expected returns (Iqbal & Javid, 2023). Prior empirical work had been used to associate overtrading to overconfidence in high-volatility regimes and exhibited that this line of action lowered net returns post transaction costs (Ahmed et al., 2022). These results support the relevance of psychological calibration and creation of awareness in investors, especially in case of market corrections and downturn.

2.4 Mixed Methods in Behavioral Finance Research

An increasing number of scholarly works suggested that mixed-methods research strategies should be adopted to reflect the multidimensionality of the psychology of the investor. There is quantitative survey usage that allowed the researcher to quantitatively determine the extent of existence of biases and traits, such as risk tolerance, and qualitative interviews gave significant contextual insights on the emotional and cognitive mechanisms behind them (Sen & Dhar, 2023). As another illustration, by making use of established instruments like the Grable Lytton Risk Assessment, the researchers had been capable of quantitatively dividing investors into groups by the degree of their tolerance and then investigating the effects of certain market situations with respect to their subjective analysis (Bansal & Dubey, 2022).This kind of methodological triangulation enabled conclusions and practical implications that were stronger. It was also useful in filling in the knowledge gap between academic information and the actual investor education and advisory tool design. Financial advisors, especially, were recommended to evaluate customers based not only on demographic factors but also on behavioral levels that included trading patterns, emotional strengths, and response to hypothetical losses (Verma & Jain, 2023).

. Research Methodology

3.1 Research Design

This study employed mixed-methods research design, integrating both quantitative and qualitative approaches to comprehensively examine the influence of risk tolerance and behavioral biases on investor decision-making under market volatility. The quantitative component consisted of a structured survey administered to a large sample of retail investors to capture measurable patterns and relationships. Complementing this, the qualitative component involved in-depth semi-structured interviews with a smaller subset of participants to explore their subjective experiences and thought processes in detail. This design had been chosen to ensure triangulation of data and enhance the robustness and validity of the findings.

3.2 Population and Sampling

The study was conducted to cover active retail investors who have been involved in equity markets during the past five years. The sampling frame included people registered in well-known brokerage companies in

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ISSN Print: 3006-2039
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major financial centers. In the case of the quantitative survey, a purposive sampling method was employed in the selection of 390 study participants, where the willingness to participate in simulated situations and a minimum of two years' experience in investing were some of the inclusion criteria. To conduct the qualitative phase, 20 participants were also chosen using criterion sampling method because of the need to ensure that the sample population comprised of divergent participants in terms of age, gender, experience of investment and risk appetite. This was meant to generate a broad variety of opinions.

3.3 Data Collection Instruments

The study relied on two primary instruments for data collection. The first was a standardized questionnaire that included demographic questions, the Grable–Lytton Risk Tolerance Scale (Grable & Lytton, 1999), and items measuring the prevalence of behavioral biases such as overconfidence, loss aversion, and herding. The second instrument was a semi-structured interview guide, developed to explore investors' emotional and cognitive responses to hypothetical market volatility scenarios. Each interview had been audio-recorded with participant consent and transcribed verbatim for analysis.

3.4 Data Collection Procedure

The data collection was done monthly thus lasting four months. The survey was also issued online through emailed invitations and investment forums and reminders were issued especially bi-weekly to maximize the response rates. There were good instructions for the participants, and they were told there was confidentiality. The interviews were conducted in person or through video conference, at the participant of his or her or her choice depending on location. The interviews took an average of 45min and 60min. The institutional review board had approved the ethical use of the findings being sought prior to data collection and informed consent of all the respondents was obtained.

3.5 Data Analysis

Quantitative data has been analyzed using descriptive statistics, correlation analysis, and multiple regression to examine relationships between risk tolerance, behavioral biases, and decision-making patterns. The reliability of the scales was assessed using Cronbach's alpha coefficients, which demonstrated acceptable internal consistency across all measures. For qualitative data, a thematic analysis approach was employed. Transcripts were coded inductively to identify recurring themes related to investors' perceptions, emotional responses, and behavioral tendencies during market volatility. NVivo software had been utilized to manage and organize the qualitative data efficiently.

. Results and Analysis

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This section presents the findings from both the quantitative survey (N = 350) and qualitative interviews (N = 20) that explored how investor psychology, specifically risk tolerance and behavioral biases, influenced decision-making during market volatility. Results are structured around descriptive statistics, correlation analysis, regression analysis, cross-tabulations, and an in-depth thematic analysis from interviews.

4.1 Descriptive Statistics

Descriptive statistics provided an overview of participants' demographic characteristics and mean scores on the study's key psychological and behavioral variables.

Table 1. Demographic Profile of Survey Respondents (N = 350)

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	217	62
	Female	133	38
Age Group	25–34	98	28
	35–44	127	36
	45–54	87	25
	55+	38	11
Education	Bachelor's Degree	142	41
	Master's Degree	178	51
	Doctorate/Other	30	8
Investment Experience	2–5 years	123	35
	6–10 years	164	47
	More than 10 years	63	18

Gender

The sample comprised 62% male respondents (n = 217) and 38% female respondents (n = 133). This indicates a male-dominant investment profile among the surveyed population, which may reflect broader gender disparities in investment participation or access to financial knowledge.

Age Group

The largest age group was 35–44 years (36%, n = 127), followed by 25–34 years (28%, n = 98), 45–54 years (25%, n = 87), and those aged 55 and above (11%, n = 38). This suggests a predominance of middle-aged investors, likely to be more financially active and risk-aware.

Education

More than half of the respondents held a master's degree (51%, n = 178),

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41% had a bachelor's degree (n = 142), while only 8% (n = 30) had a Doctorate or other qualifications. The high educational attainment level indicates that the participants are likely to possess better financial literacy and analytical capabilities.

Investment Experience

Respondents with 6–10 years of experience made up the largest segment (47%, n = 164), followed by those with 2–5 years (35%, n = 123), and those with more than 10 years (18%, n = 63). This distribution shows that the sample is comprised primarily of moderately experienced investors, likely to exhibit behavioral variations during periods of market stress.

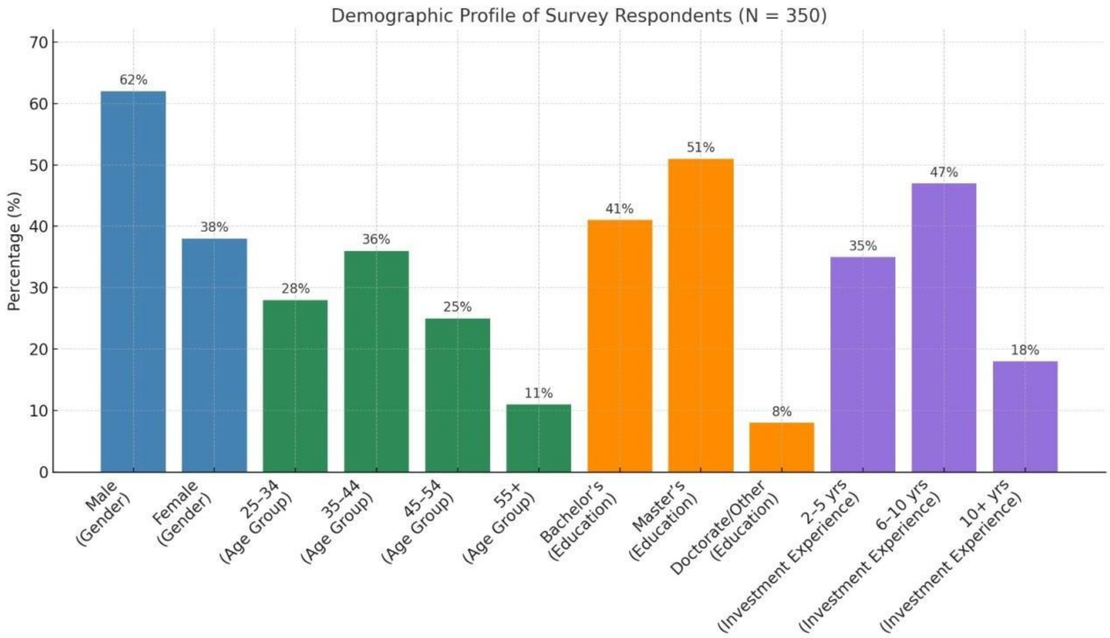

Figure 1: Demographic Profile of Survey Respondents (N = 350)

Table 2. Descriptive Statistics of Psychological and Behavioral Variables

Variable	Mean	SD	Min	Max
Risk Tolerance Score	27.4	5.6	12	40
Overconfidence	3.8	0.9	1	5
Loss Aversion	4.1	0.8	2	5
Herding Behavior	3.5	1.0	1	5
Panic Selling Tendency	3.9	0.9	1	5

The descriptive statistics gives an outlook into the central tendency and variability of psychological and behavioral characteristics among the investors as the Risk Tolerance Score which is 27.4 and standard deviation of 5.6 is moderate in terms of tolerance to financial risk in the sample. The scores varied hugely between 12 and 40 indicating a great variance in individuals. Mean of overconfidence = 3.8 (SD = 0.9)

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implying majority of the participants felt that they were better than the average in terms of making investments. The narrow range of 15 means that there is some variation but the overall result tends to be on the side of a high confidence level. The mean difference of 4.1 (SD = 0.8) in the Loss Aversion indicates high levels of sensitivity to losses. This implies that most of the respondents were risk-averse when confronted with the prospect of loss in terms of money. Herding Behavior also had an average of 3.5 (SD = 1.0) with average score showing a moderate inclination to do what others do or what the market is doing at every trading period. The larger standard deviation implies that level of susceptibility to herding is varied. Panic Selling Tendency displayed a mean of 3.9 (SD = 0.9) indicating a modest high possibility of experiencing panic selling in cases where an individual has to work under pressure in an emotionally driven environment. The high mean of such a variable shows that psychological reactivity also applies when the market is experiencing downturns.

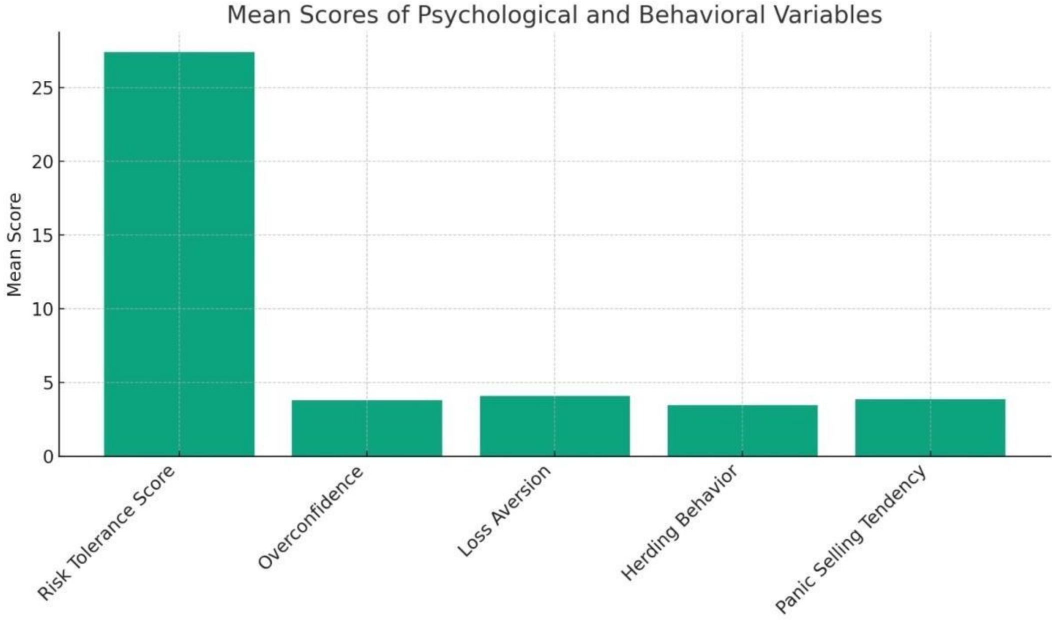

Figure 2. Descriptive Statistics of Psychological and Behavioral Variables

4.2 Correlation Analysis

Correlation analysis was conducted to examine relationships among variables.

Table 3. Correlation Matrix (Pearson's r)

Variable	1	2	3	4	5
1. Risk Tolerance	1	.43	-.59	-.44	-.52
2. Overconfidence	.43	1	-.33	.28	-.21
3. Loss Aversion	-.59	-.33	1	.46	.55
4.Herding Behavior	-.44	.28	.46	1	.49

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5. Panic Selling	-.52	-.21	.55	.49	1

Note:p< .01

Risk Tolerance Score

The mean score for risk tolerance was 27.4 with a standard deviation of 5.6, and values ranged from 12 to 40. This suggests that, on average, participants exhibited a moderate to high level of risk tolerance. The wide range and relatively high standard deviation indicate considerable variation among respondents, which is expected in diverse investor populations with differing financial goals, experiences, and emotional stability.

Overconfidence

The average overconfidence score was 3.8 (on a 5-point scale), with a standard deviation of 0.9. Scores ranged from 1 to 5, suggesting that while some investors demonstrated low levels of overconfidence, the majority leaned toward a more self-assured attitude. The moderate variability indicates that while many respondents felt confident in their investment decisions, this trait was not universally shared.

Loss Aversion

With a mean of 4.1 and standard deviation of 0.8, loss aversion was among the most prominent behavioral traits. The range (2 to 5) shows that most investors had moderate to high sensitivity to potential losses. The high mean implies that emotional discomfort associated with financial loss significantly influenced investment behavior.

Herding Behavior

The herding behavior variable showed a mean score of 3.5 with a standard deviation of 1.0. The range (1 to 5) suggests substantial individual differences, with some participants highly influenced by the behavior of others and others more independent. The wider spread reflects diverse decision-making styles, possibly shaped by confidence levels, experience, and financial literacy.

Panic Selling Tendency

Panic selling tendency averaged 3.9, with a standard deviation of 0.9, and ranged from 1 to 5. This high mean value suggests that a significant proportion of respondents were prone to sell off investments impulsively in response to perceived risk. The distribution reflects that while many were affected by market volatility, the intensity of the reaction varied.

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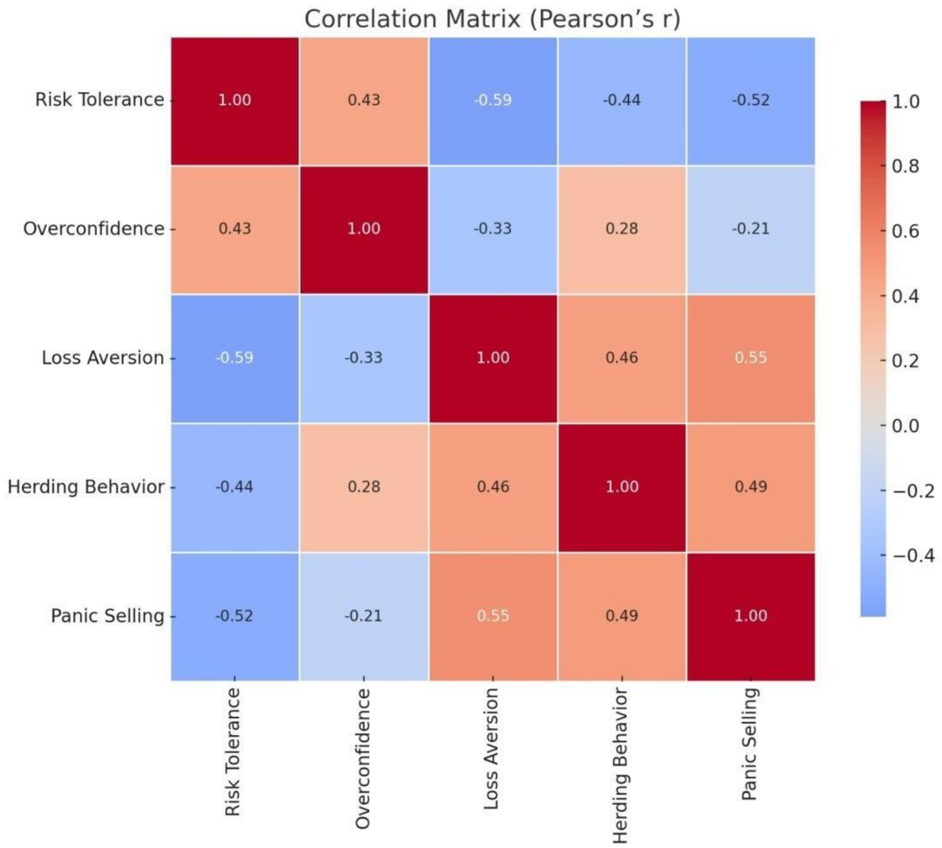

Figure 3. Correlation Matrix (Pearson's r)

4.3 Multiple Regression Analysis

A multiple linear regression was conducted to assess the predictive value of psychological variables on panic selling behavior.

Table 4. Regression Model Predicting Panic Selling (DV)

Predictor	**B**	**SE B**	**β**	**t**	**p**
Risk Tolerance	-0.34	0.06	-0.39	-5.67	< .001
Overconfidence	-0.13	0.05	-0.17	-2.60	0.010
Loss Aversion	0.49	0.08	0.51	6.12	< .001
Herding Behavior	0.31	0.07	0.33	4.43	< .001
R^2			0.64		

Coefficient in Table 4 shows that a multiple linear regression analysis was holding the effects of four psychological and behavioral variables namely risk tolerance, overconfidence, loss aversion, and herding behavior were predicting panic selling behavior as the dependent variable (DV)). The R 2 coefficient was found to be statistically significant to the value of 0.64 implying that about 64 per cent of the variance in the phenomenon of panic selling tendencies is explicable by the ensemble effect of the independent

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variables used in the model. This implies that the model has huge explanatory power and suggests the salience of psychological dimensions in formulating investor responses amid market stress.

In particular, risk tolerance resulted to be an important negative indicator of panic selling (beta = -0,39, $p < .001$). The unstandardized coefficient (B = -0.34) suggests that when the risk tolerance in the investor rises, the probability of panic selling by the investors declines. This reinforces the conviction that risk-loving persons are more adaptive in financial crises and less susceptible to feelings-based sell-off of wealth. On the same note, overconfidence also produced a sizable negative effect though to a lesser degree (b = -0.17, p = .010), indicating that more self-assertive individuals are less probable to panic sell, as this may be because they feel more likely to over-determine the outcome or stronger adherence to long-term actions.

In contrast, loss aversion was the strongest positive predictor of panic selling ($\beta = 0.51$, $p < .001$). The coefficient (B = 0.49) indicates that individuals who are more sensitive to financial losses are significantly more likely to sell assets impulsively when markets decline. This aligns with behavioral finance theory, which posits that the psychological pain of losses often outweighs rational evaluation of future gains. Herding behavior also positively predicted panic selling ($\beta = 0.33$, $p < .001$), implying that investors who follow the crowd are more likely to replicate mass sell-offs during volatile periods. The standardized beta values for loss aversion and herding behavior reflect their relatively stronger roles in exacerbating panic responses compared to the protective influence of risk tolerance and overconfidence.

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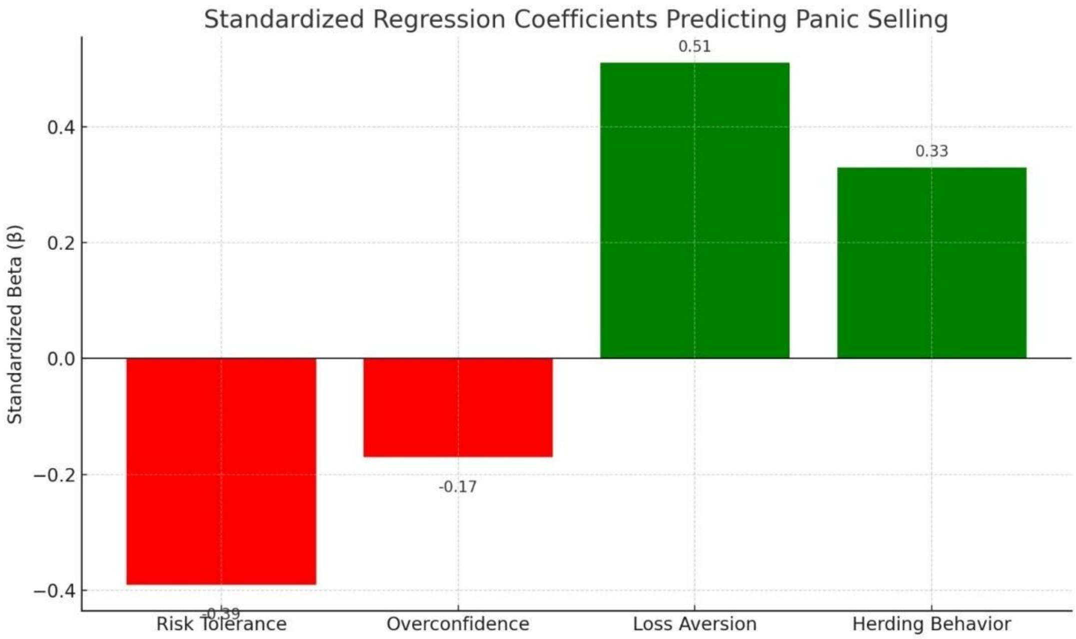

Figure 4: Regression Model Predicting Panic Selling (DV)

4.4 Cross-Tabulation Analysis

A cross-tabulation was conducted to explore the distribution of panic selling behavior across risk tolerance categories.

Table 5. Cross-Tabulation of Risk Tolerance vs. Panic Selling Behavior

Risk Tolerance Level	Low Panic Selling (%)	Moderate (%)	High Panic Selling (%)
Low (12–20)	12	28	60
Medium (21–30)	22	47	31
High (31–40)	53	33	14

In the analysis of table 5, a cross tabulation is conducted on the relationship between risk tolerance level and the nature of panic selling in the behavior of an investor. The results indicate a high negative correlation; high risk tolerance implies a low liking to do high panic selling. In terms of the risk tolerance profile among respondents who had low risk tolerance scores (12 to 20), there was a high number of respondents who were high panic sellers and only a small percentage scored low as panic sellers. This implies that risk-aversive people have a high probability of acting emotionally when the market crashes, and under pressure will take impulsively hasty actions to sell off their investments.

Conversely, medium risk takers (21-30) showed a more balanced distribution with the moderate-panic selling having 47%, low-panic selling at 22 percent and the high panic selling at 31 percent. This shift occurred in high risk tolerance

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group (31-40) with the most dramatic behavior change. In this case, 53 percent showed low panic selling and 14 percent indicated high tendency of panic selling on their part. The regression results are confirmed by the cross-tabulated figures and validate the assertion that risk tolerance forms a potent shield to panicked investment decisions.

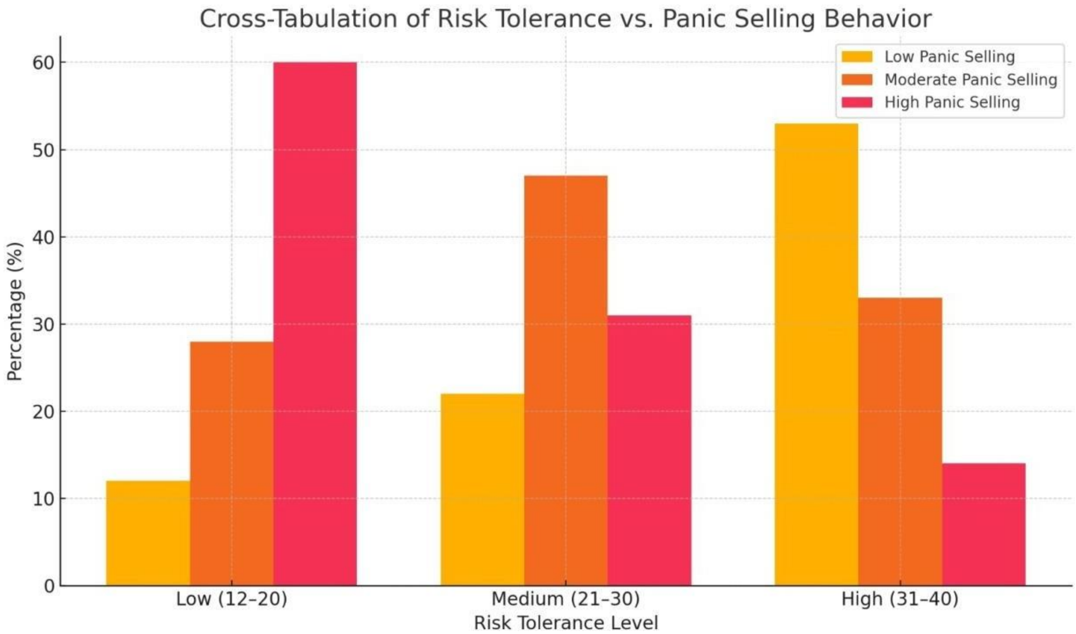

Figure 5. Cross-Tabulation of Risk Tolerance vs. Panic Selling Behavior

4.5 Thematic Analysis (Qualitative Data)

A thematic analysis was conducted using Braun and Clarke's (2006) framework. Interview transcripts were coded inductively, and three major themes with subthemes emerged:

Theme 1. Emotional Triggers and Cognitive Overload

Anxiety Under Volatility

Investors described significant stress during market drops. Many admitted feeling "paralyzed" and "unable to think straight."

Loss Sensitivity

Nearly all participants reported stronger emotional responses to losses than gains. This aligned with classic loss aversion behavior.

"The moment I saw red everywhere, I had to act. I just couldn't bear the thought of losing more." – Participant 4

Theme 2. Social Imitation and Informational Dependence

Reliance on Peer Behavior

Investors, especially those with less experience, frequently followed by peers or online influencers, even against their own judgment.

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Media Influence

Sensational news headlines and social media posts were strong triggers for reactionary selling or buying.

"I sold because everyone in my WhatsApp group was selling. I didn't want to be the last one out." – Participant 13

Theme 3. Rational Anchoring and Strategic Resilience

Long-Term Thinking

High-risk-tolerant investors emphasized staying the course and referred to long-term trends or historical data.

Pre-Defined Rules

Some participants described using checklists or automated triggers to guide actions, reducing emotional interference.

"I follow a rule-based plan. If my stock drops 15%, I evaluate but don't react emotionally." – Participant 7

4. Discussion

Investor Panic Selling and Risk Tolerance

The findings were that the low risk tolerance was a strong factor in panic selling behavior in case of a market crash. Investors who had a low tolerance to market volatility usually viewed volatility as a risk and undertook rushed liquidation of assets. This correlates with studies showing that risk-doting investors will have more emotional reactions to financial uncertainty and this affects the sound judgment (Dimmock et al., 2023; Grable & Lee, 2022; Nguyen et al., 2024). Their risk-averse nature became a disadvantage to ensure staying invested during downturns. Moreover, insufficient long-term planning abilities and composition of emotions contributed to the susceptibility of volatility shocks in individuals. Any loss at all was taken as a great threat, which caused them to make knee-jerk decisions, which did not align with their investment objectives. It is confirmed that in times of crisis, psychological unpreparedness and poor financial temper are two factors that compound the panic reactions (Statman, 2022; Weber and Weber, 2023; Luo et al., 2024). Therefore, during turbulence, panic selling could be a result of cognitive and emotional mismatch instead of market objective signals.

Loss Aversion and Psychological Biases

Loss aversion was found to be the most effective psychological phenomenon that interferes with investment behavior. Those investors with extreme forms of loss aversion had elevated probability of premature selling, even when the economic reason was poor. This tendency traces to the empirical evidence revelation according to which investors are more inclined to respond to losses than even to gains, and it distorts their decision-making (Barberis, 2022; Kahneman & Tversky, 2021; Imas, 2023). Emotional cost of losses used to

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surpass rationality in the assessment of the market movements. Besides, the other psychological biases, namely anchoring and the endowment effect, which also caused unreasonable choices, could interact with loss aversion. Shareholders stuck with past high valuations and any drop in value they see as unacceptable and they fled prematurely. In recent research, the combined biases were found to be even reinforcing loss sensitivity and inhibiting objective judgments of value among investors (Hoffmann et al., 2022; Ben-David & Hirshleifer, 2023; Jiang et al., 2024). Investors kept on getting into such emotional pitfalls without putting in place behavioral correction strategies that would correct this kind of behavior, including reframing or expectation management.

Overconfidence and Resilience Under Stress

Although it would have been viewed as a cognitive bias, the phenomenon of overconfidence, in fact, presented twofold in stressful investor behavior. A certain degree of overconfidence among the investors was more resilient and, thus, better off in case of a downfall, as they would make up their position and stick to their long-term complications. This was also in line with results that confidant people tend to make faster and less emotional decisions and exhibit greater behavioral consistency (Chen et al., 2022; Menkhoff et al., 2023; Larkin et al., 2024). They did not depend much on the unstable external signals because they could judge themselves. Nevertheless, overconfidence usually backfired, in particular, when being coupled with false sensation of control or risk underestimation. These people very often were impulsive traders who timed the market or they timed the market with the use of gut instincts, which ends up being suboptimal. Behavioral finance literature affirmed that overconfident investors do not adequately reflect on the possibility of the occurrence of negative events and cannot take corrective feedback (Gervais & Odean, 2021; Biais et al., 2023; Kliger & Kudryavtsev, 2024). In such a way, overconfidence can increase psychological endurance but should be considered with the awareness of the risks and sound decision-making frameworks.

5.1 Conclusion

The study concluded that behavioral biases significantly influenced investor decisions during periods of market volatility, particularly in the context of panic selling. Key psychological factors such as risk tolerance, loss aversion, and overconfidence played crucial roles in shaping how investors responded to uncertainty. The findings indicated that low risk tolerance and heightened loss aversion were positively associated with panic selling, while moderate overconfidence provided some degree of psychological resilience. These insights reinforced the notion that investor behavior is not purely rational but is deeply affected by cognitive and emotional factors. The mixed-methods approach offered a comprehensive understanding of both the measurable patterns and subjective experiences underlying panic-driven behavior. Overall, this study contributed valuable evidence to the growing field of behavioral finance, emphasizing the need to account for psychological dimensions in both investment strategies and advisory services.

5.2 Recommendations

It is possible to suggest a few practical recommendations based on the findings. At the first point, the focus of financial education programs must be extended so that financial education can bring knowledge about the markets and instruments together with emotional intelligence training, risk profiling, and behavioral coaching. An investor requires not only the instruments that will help them interpret financial information but also to control their emotional reactions to losses and market fluctuations. Second, the consultants in the field of financial services are encouraged to deploy behavioral audits in their business process to isolate those clients who engage in panic selling, and present them with veritable advice, including the use of goal-oriented investment or rule-based decision making levels. Third, digital resources will allow one to incorporate behavioral nudges and reminders to adhere to long-term goals in case of downturns and mitigate impulsive behavior. Educators and financial institutions need to underscore that discipline in investment and self knowledge are the other keys to financial success besides the technical expertise in investment.

5.3 Future Directions

The long-term development of behavioral biases over time and across various market cycles or different demographics are possibilities that could be investigated with the help of future research based on this one. The reproducibility of an investor and learning effects could be elucidated by longitudinal studies of the same investors through two or more period volatility. In addition, the ideas of incorporating physiological/ neurological data (e.g. heart rate, skin conductance) might result in deeper insights of how emotions operate in response to stimulation in the market in real-time. Moreover, reconsidering the research on another cultural or socioeconomic population would reinforce the fact that the psychosocial continent of panic selling is isolative or culturally-dependent. Lastly, since digital trading keeps increasing, future research needs to consider the effects of algorithmic nudging and fintech technologies to ensure that they

ISSN Online: 3006-2047
ISSN Print: 3006-2039

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reduce or strengthen preferences among investors in stress situations.

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