

Between Fear and Greed: Behavioral Biases and In-vestment Decision-Making Among Millennial Retail In-vestors

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Abstract: *An increase is observed in the participation of millennial retail investors in the fi-nancial markets through digital platforms, where cognitive and social biases can systematically distort decision-making. This study addresses how behavioral bi-ases shape millennial investment decisions using Partial Least Squares Structural Equation Modelling (PLS-SEM). A model reflecting three latent constructs be-havioral bias (BB), trading and herding behaviour (TH), and risk perception and loss-aversion shifts (RP) of 80 millennial investors was estimated on survey data. The measurement model demonstrates strong reliability and validity (composite reliability 0.902–0.924; AVE 0.648–0.709). Structurally, behavioral biases exert-ed a strong, strategically well-powered effect on both trading and herding behav-iour ($\beta = 0.761$, $f^2 = 1.38$, $R^2 = 0.579$) and on risk perception and loss-aversion shifts ($\beta = 0.739$, $f^2 = 1.20$, $R^2 = 0.545$), with achieving power ≈ 1.000 at the 1% level. The results support all three hypotheses: overconfidence is associated with excessive trading and weaker risk assessment, social influence with herding, and loss aversion with risk-averse shifts under volatility. Findings underline the sali-ence of behavioral factors for investor education and platform design.*

Keywords: Behavioral finance, retail investors, millennials, overconfidence, herding, loss aversion, PLS-SEM, structural equation modelling.

Introduction

Behavioral patterns and biases of investors have a paramount influence in investment decisions, research studies suggest that human emotion, global instability and market knowledge play a vital role in financial choices. With the advent of disruptive technologies there is a seismic shift in investors' approach, influencing their investment behaviour, AI and neural networks have the potential to mitigate the rising concerns of behavioral biases (Talwar et al., 2021). Agents in finance often categorize investors based on shared patterns and traits, allowing for more effective intervention strategies. In recent years generational cohort categorization has gained a significant preference over traditional classification including gender, income and status in determining global economics. Millennial Investors (born in between the years 1981 and 1996) have become a prevalent part of the global economic events such as the 2007 global financial crisis. Understanding their distinctive and powerful behavioral biases and cognitive thinking patterns is essential to navigate important market shifts (Altaf & Jan, 2023b). The various psychological and economic factors influencing the retail investors of the Indian equity market will be explored in this research. Focusing on the specific behavioral biases of these investors that may impact asset investment and decision-making choices. Many investors' financial decisions are altered by their emotional and psychological responses, regardless of the independent analysis and intentional asset diversification. Exploring strategies that assist in limiting irrational behaviors is necessary to support long-term profits and understand the future generations' division-making strategies (Ahuja & Kumar, 2024). Portfolio investment managers categorize clients to better identify patterns and develop specialized products as portrayed by Figure 1.



Figure 1. Generational Investment Patterns and Behavioral Biases

Demographic classifications like income, gender and class are becoming obsolete and the market is shifting towards generational cohort classification to influence modern market trends. This classification allows for a deeper understanding of the psychological patterns and required interventions (Altaf & Jan, 2023d). Millennial investors decision-making has been significantly impacted by past economic events such as the 2007 financial crisis, resulting in demand for diverse assets varying from equities to bonds. Their unique financial behaviors and psychological traits make them more vulnerable to specific cognitive and emotional biases, influencing their financial choices. Familiarizing these traits is essential for financial agents to

better understand millennial patterns and future macroeconomic trends caused by them (Altaf & Jan, 2023c).

The differentiated behavioral biases and decision-making patterns of millennial investors in the financial market will be explored in this research. How specific stock selection can be determined by information overload and impulsive decisions. Psychological drivers such as brand loyalty and pleasure-seeking impact investors' response to gamified platforms and real time data. This study focuses on investor psychology and their financial strategies (NMahalakshmi & Munuswamy, 2022). Financial choices of millennial retail investors are often influenced by psychological tendencies like groupthink and extensive self-assurance. Modern investors' financial investment patterns are influenced by behavioral biases as illustrated in Figure 2 (Sattar et al., 2020). Concepts such as bounded rationality including limited cognitive capacity and information along with demographics such as income and gender prove investors' irrational decisions. Understanding these patterns allows financial regulators to evaluate the market condition and financial outcomes (Raj, 2024).

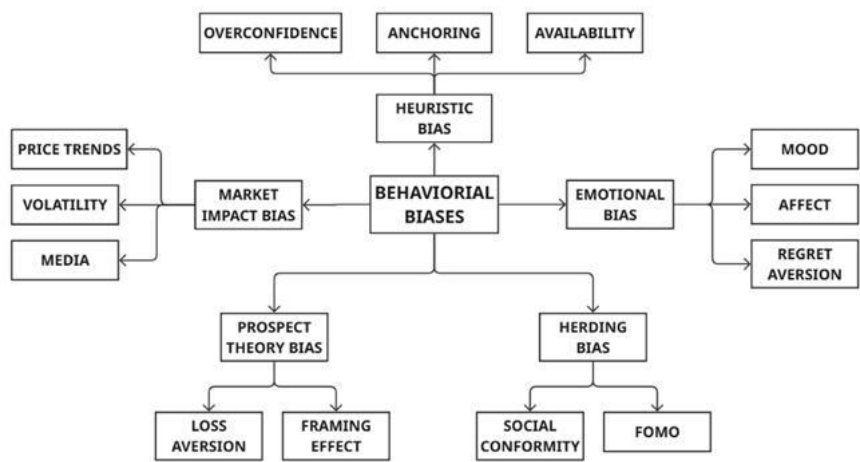


Figure 2. Behavioral Biases in Millennial Retail Investors

Unlike the previous generations, the millennial cohort makes capital decisions while actively considering technological fluency, demographics and distinct psychological tendencies that collide with classic economic theories. Herd mentality and framing effect are additional biases to heuristic biases that drive decisions. Understanding these significant patterns is important for financial professionals to improve education and limit irrational behaviors for reduced fluctuations in the market (G, 2021). Recent financial research suggests that psychological triggers and cognitive shortcuts, especially in millennials, can lead to irrational investment decisions which contradict traditional financial theory that is driven by utility maximization. Digital trading platforms and social media often worsen biases like herd mentality and overconfidence and portray the contrast between classic economics theory and irrational reality of modern investment patterns (Reddy et al., 2026). Exploring the shift from standard finance to behavioral finance helps understand how traditional theory assuming perfectly rational behaviour contrasts with a multidisciplinary approach, where psychology and economics are

combined to better understand human financial choices. Identifying these emotional and cognitive factors help recognize the effect on market stability and establish financial paradigms (Sharma et al., 2021). Most traditional economics theories neglect market fluctuation such as bubbles and crashes, focusing only on the rational decisions and outcomes. However, behavioral finance including psychological biases and emotions helps explain the irrational retail investment choices, principally in millennials, uniquely identified by their preferences in digital technology and social media (Bihari et al., 2022).

The aim of this investigation is to analyses the influence of behavioral biases including overconfidence bias, loss aversion and herding tendencies on investment decision-making patterns of millennial retail investors, with particular attention to how cognitive heuristics and social influences interact within a digitally mediated, fintech-enabled investment environment, this research seeks to assess the conceptual pathway linking gender-based anchoring and peer influence to herding behaviour, and to evaluate how perceived risk, market volatility, and prospect-theoretic loss weighing shape frequency, risk assessment quality and reliance on diversified analysis among this cohort.

The remainder of this paper is structured as follows. Section 2 presents a comprehensive review of the extant literature on behavioral finance and investor decision-making, situating the study within existing theoretical and empirical frameworks. Section 3 outlines the research questions and hypotheses guiding the investigation, drawing on identified gaps in the literature. Section 4 details the research methodology, including the sampling approach, data collection instruments, and analytical techniques employed. Section 5 presents the results of the empirical analysis and offers a discussion of the key findings in relation to existing theory. Finally, Section 6 concludes the paper by summarizing the principal contributions, discussing theoretical and practical implications, acknowledging the study's limitations, and proposing directions for future research.

Literature Review

Behaviors such as excessive trading, weaker risk assessment, reliance and ignorance of diversified analysis are encouraged by overconfidence bias, which is often displayed in millennial retail investors. Investment decisions must be based on details such as financial capability, experience and professional knowledge rather than heuristics or sentiments to prevent costly errors, particularly in emerging markets (Ahmad & Shah, 2020).



Figure 3. Conceptual Framework of Behavioral Bias Influencing Millennial Decisions

When making investment decisions, representative heuristic considerations three factors: the search rule, stopping rule and decision rule. The operations of this heuristic are influenced by experience, intuition and overconfidence. Experience leads to analogical comparisons, intuition assists competing interpretations and overconfidence affects search duration, costs and decision thresholds (Galavotti et al., 2021).

As portrayed in Figure 3 behavioral biases such as overconfidence, loss aversion, anchoring, confirmation, herding, disposition, framing, and regret aversion may lead to variances in rationality assumed in traditional finance. These biases can cause suboptimal portfolio decision-making, misunderstood judgement and intensify market volatility. These phenomenon's highlight the importance of investor education, targeted market intervention and adaptive strategies (Sathya & Gayathri, 2024). Millennial retail investors, shaped by digital-native access to markets and information, frequently exhibit overconfidence bias and inflated belief in their own analytical ability relative to actual investment outcomes. This manifests as excessive trading frequency, underestimation of risk, and overreliance on self-generated forecasts rather than diversified analysis. Common investment mistakes due to behavioral biases can be categorized according to cognitive processes (how investors think) and emotional responses (how investors feel). Additionally, social factors may also affect financial outcomes. Studies have determined five steps that assist investors overcome consistent errors and identify future investor behaviors (Baker & Nofsinger, 2002). The findings revealed that anchoring highly influenced investors decision-making. Particularly, females were observed to be more likely to anchor than their male counterparts. Moreover, a higher level of financial knowledge did not help to reduce the possibility of anchoring; it rather increased it. The study adds to the body of knowledge on the influences of behavioral biases in the sub-region to make investors aware of their biases in order to minimize the influence of these biases on their investment decisions (Owusu & Laryea, 2022).

Technological changes, social media, financial technology, risk perception, financial literacy and peer influence have shaped millennial investment behaviors. In rising economies, market access and participation has significantly increased due to increase in digital platforms, social and cultural factors. Pre-existing studies provide limited knowledge on psychological, sociological and cultural foundations as they rely heavily on quantitative, survey-based methods. This research uses a combination of technological, cultural and psychological measures to provide an understanding of millennial investor behaviour in rising economies (Zega & Satato, 2025). In recent years access to real-time information, fintech applications, algorithmic recommendations, online financial communities have expanded and therefore investment decision-making has rapidly changed due to digitalization. The increase of digital platforms has accelerated investment decisions however the increased exposure often leads to information overload, herding and speculation risks. Through the use of non-linear relationships and interaction effects, studies have concluded an immediate need for investor education, ethical fintech design and regulatory awareness (AI-Based Predictive Modelling of Digitalization Effects on Investment Decisions of Gen Z Investors, 2026). Contradicting the Efficient Market Hypothesis which assumes rational behaviour, Gen Z and Baby Boomers tend to follow herd behaviour and information cascade which influences their mutual fund selection. Various differences exist among both generations including information sources, decision-

making speed, social proof, portfolio composition and turnover. Baby Boomers rely on conventional and institutional guidance, whereas Gen Z is more inclined towards digital platforms, exhibiting faster decision and higher turnover. This shift proves the concept of “Digital Stampede” and implications for advisors, fund managers and policymakers (Rajak & Pandey, 2026). To help retail investors identify and mitigate behavioral biases when making investment decisions, the use of AI-enabled digital advisory service has been encouraged. This service allows agents such as investors, fintech providers and policy makers to practice and support development of ethical, transparent and regulation-compliant standards when making investment decisions (Maheshwari & Samantaray, 2025).

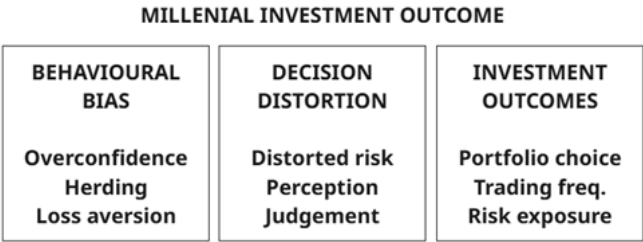


Figure 4. Pathway From Behavioral Bias to Millennial Investment Outcomes

The importance of such AI-driven support becomes clear when considering the Equity Premium Puzzle, which can be explained through behavioral bias concepts such as loss aversion and mental accounting. Experiments across various investor groups were conducted to support this theory. Unexpectedly, professional CBOT traders displayed stronger myopic loss-aversion tendencies than students, proving that trading expertise does not eliminate behavioral biases when making investment decisions (Haigh & List, 2005). Results from an international survey experiment involving financial professionals and laymen shows that perceived financial risk is based more on return skewness and the probability of losses rather than variance alone. Volatility was the dominant conventional risk measure; however, it did not regularly affect professional risk perception. Investment propensity, with resembling patterns across countries and occupational groups were predicted by skewness and loss probability suggest that digital investors’ loss-driven reaction may demonstrate comprehensive limitation in conventional risk assessment as seen in Figure 4 (Holzmeister et al., 2020). A core concept of Prospect Theory is loss aversion which explains why investors weigh losses more heavily than equivalent gains. Neuroscience and computational modelling have found how norepinephrine and dopamine links directly to loss sensitivity and reward-oriented risk taking respectively. Additionally, it provides a clear distinction between anticipated and immediate response from longer-term reactions to gains or losses among millennial retail investors (Sokol-Hessner & Rutledge, 2018). To understand the market-level consequences of loss aversion a behavioral agent-based asset-pricing model was used. Unlike bias-free models, this framework very carefully provides key empirical features of financial time series. Different levels of loss aversion cause different behaviour changes of traders in a competitive market. The model also captures empirical features such as heavy-tailed returns, volatility clustering, gain-loss asymmetry and memory (Pruna et al., 2019).

Research Methodology

A large cohort of millennial retail investors has been drawn into equity and derivative markets following the rapid rise of commission-free trading. Behavioral finance suggests that such investors are susceptible to systemic cognitive and social biases overconfidence, herding, and loss aversion that can distort trading frequency, risk assessment, and response to market volatility. In a digitally native cohort, it is important to understand how these biases operate for financial-education policies and investor protection. This study models behavioral biases as a driver of two behavioral outcomes and tests three hypotheses:

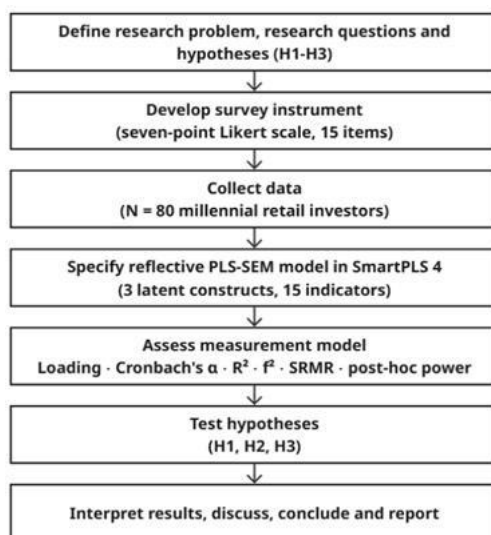


Figure 5. PLS-SEM Research Methodology Procedural Flow

Research Questions

1. RQ1. How does overconfidence bias influence excessive trading frequency and the quality of risk assessment among millennial retail investors?
2. RQ2. To what extent do social influences including peer effects and gender-based anchoring contribute to herding behaviour in millennial investment decisions?
3. RQ3. What is the relationship between loss aversion, perceived financial risk, and market volatility in shaping the investment behaviour patterns of millennial retail investors?

Hypothesis

1. H1. Overconfidence bias is positively associated with excessive trading frequency and negatively associated with quality of risk assessment among millennial retail investors.
2. H2. Social influence factors including peer effects and gender-based anchoring, are positively associated with herding behaviour in millennial investment decision-making.
3. H3. Loss aversion is positively associated with risk-averse behavioral shifts among millennial retail investors, particularly under conditions of heightened market volatility.

A. Research Design and Sample

A quantitative, cross-sectional survey design was followed. Data was collected from 80 millennial retail investors using validated multi-item, seven-point Likert scales adapted from the behavioral -finance literature. Fifteen indicators were modelled reflectively across three latent constructs, and the model was estimated in SmartPLS 4 using the PLS-SEM algorithm.

B. Construct Operationalization

Behavioral Biases (BB) is the external construct, with reflective indicators capturing overconfidence, social/anchoring susceptibility, and loss-aversion tendencies (indicators 1–5). Trading and Herding Behaviour (TH) captures excessive trading frequency and socially driven herding (indicators 6–10). Risk Perception and Loss-Aversion Shifts (RP) captures risk-assessment quality and risk-averse behavioral shifts under volatility (indicators 11–15). Modelling the biases as a single higher-order exogenous construct is a simplification made for parsimony and is discussed in the limitations.

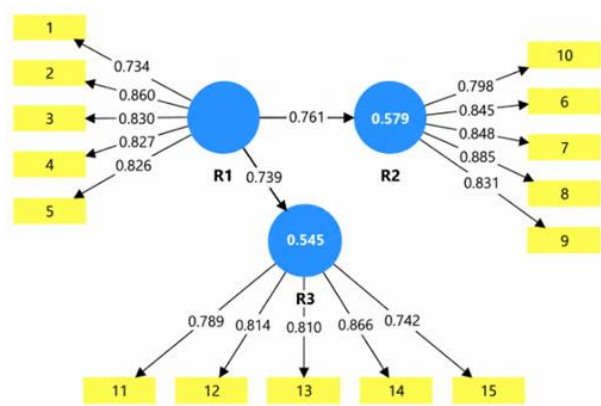


Figure 6. PLS SEM Framework for Behavioral Biases for Millennial Investors

C. Analytical Approach

Indicators including Cronbach’s alpha, composite reliability (ρ_a , ρ_c), and average variance extracted (AVE) were incorporated to assess the measurement quality while the Heterotrait–Monotrait ratio (HTMT) and the Fornell–Larcker criterion was used for discrimination validity. The structural model was assessed using path coefficients, f^2 effect sizes, R^2 , model fit (SRMR), and a post-hoc power analysis.

Figure 6 illustrates the P[LS-SEM framework path model. The three blue circles represent the latent constructs: behavioral biases (R1), trading and herding behaviour (R2), and risk perception and loss-aversion shifts (R3) which are abstract variables not measured directly but inferred from the observed data. The fifteen yellow boxes represent the measured indicators (survey questions), each linked to its construct by an outer loading (0.734–0.885), confirming that every item reliably reflects its construct. The arrows connecting the circles represent the structural path coefficients ($R1 \rightarrow R2 = 0.761$; $R1 \rightarrow R3 = 0.739$), while the values within R2 (0.579) and R3 (0.545) indicate the proportion of variance (R^2) explained by behavioral biases.

The model is reflective in specification as all indicator arrows point from the constructs to the items.

Results

Measurement Model

All constructs exceeded reliability and convergent-validity thresholds. Cronbach's alpha ranged 0.865–0.897, composite reliability (ρ_c) 0.902–0.924, and AVE 0.648–0.709 (all above 0.50). Indicator loadings ranged 0.734–0.885, all above the 0.70 benchmark (Table I).

Table I. Construct Reliability and Convergent Validity (N = 80)

Path	β	f^2	R^2 (endo.)	Power 1%	Result
BB $\rightarrow$ TH	0.761	1.38	0.579	≈ 1.000	Supported
BB $\rightarrow$ RP	0.739	1.2	0.545	≈ 1.000	Supported

Mapping to hypotheses: the BB $\rightarrow$ TH path ($\beta = 0.761$) supports H1 (excessive trading) and H2 (herding), as trading-frequency and herding indicators load on TH; the BB $\rightarrow$ RP path ($\beta = 0.739$) supports H1 (risk-assessment quality) and H3 (loss-aversion-driven risk-averse shifts under volatility), as risk-assessment and volatility-response indicators load on RP. All three hypotheses are therefore supported by strong, well-powered structural relationships.

Discussion

The structural model provides strong support for all three hypotheses, with behavioral biases rising as a dominant determinant of millennial investment behaviour. The exogenous construct explained a substantial share of the variance in both endogenous constructs 57.9% for trading and herding behaviour and 54.5% for risk perception and loss-aversion shifts and both structural paths were large, positive, and statistically well-powered (achieved power ≈ 1.000 at the 1% level), indicating that the observed relationships are robust rather than artefacts of sampling.

Regarding RQ1 and H1, overconfidence bias directly correlates with excessive trading and weaker risk assessment as confirmed by the results. The strong path from behavioral biases to trading and herding behaviour ($\beta = 0.761$, $f^2 = 1.38$) reflects the tendency of overconfident investors to overestimate the accuracy of their imperfect information and trade more frequently than is warranted, while the equally strong path to risk perception ($\beta = 0.739$, $f^2 = 1.20$) captures the corresponding deterioration in the quality of risk assessment. This dual effect is consistent with established evidence that overconfident retail investors trade excessively and to the detriment of their returns and supports H1 in both of its stated directions.

Regarding RQ2 and H2, the findings indicate that social influence considerably contributes to herding behaviour. Due to peer effects and gender-based anchoring load on the trading and herding construct, the significant behavioral -biases $\rightarrow$ trading and herding path ($\beta = 0.761$)

demonstrates that socially driven imitation is a significant component of millennial investment decision-making. Investors influenced by the observed actions of peers, and anchored to socially salient reference points, tend to conclude on similar decisions rather than independent, information-based ones, the defining feature of herding. H2 is therefore supported.

Regarding RQ3 and H3, the results support the thesis that loss aversion impacts risk-averse behavioral shifts under volatility. The strong path from behavioral biases to risk perception and loss-aversion shifts ($\beta = 0.739$, $f^2 = 1.20$) reflects the asymmetric weighting of losses relative to gains described by prospect theory, whereby the prospect of loss under heightened market volatility prompts disproportionately risk-averse adjustments. Loss aversion is not a marginal influence but a central mechanism in how millennial investors recalibrate risk is indicated by the high variance in this construct ($R^2 = 0.545$). H3 is thus supported. In conclusion, the three findings converge on a consistent account: behavioral biases function as a pervasive and powerful driver across both the evaluative (risk perception) and transactional (trading, herding) aspect of millennial investment behaviour and decisions. The extent of the effects, with effect sizes well above conventional thresholds for a large effect, underscores that these are central features of how this cohort makes financial decisions, not peripheral tendencies.

Conclusion and Future Scope

Upon analysing data from 80 millennial retail investors using the PLS-SEM, this study concludes that behavioral biases strongly and significantly from both trading/herding behaviour ($\beta = 0.761$) and risk perception and loss-aversion shifts ($\beta = 0.739$), with strong validity and reliability and near-unity statistical power. All three hypotheses were supported: overconfidence corresponds with excessive trading and weaker risk assessment; social influence with herding; and loss aversion with risk-averse shifts under volatility. Thus, an efficient and powerful explanation of millennial investment decision-making is offered by behavioral factors.

Future Scope and Limitations

Sample and generalizability: The considered sample size of 80 respondents is modest; however, a larger, multi-regional sample would strengthen external validity and enable bootstrapped significance testing with the post-hoc power analysis.

- Bias disaggregation: A disaggregation model with separate overconfidence, social-influence, and loss aversion constructs would test each hypothesis's unique path rather than modelling biases as single higher-order construct, which limits attribution to specific biases.
- Discriminant validity: The TH-BB HTMT (0.855) warrants item refinement to sharpen construct separation.
- Moderation and design: Future work could test market volatility and gender as explicit moderators and complement self-reporting with behavioral trading data.

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