TPM Vol. 32, No. S6, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

BEHAVIORAL DETERMINANTS OF INVESTMENT DECISIONS: A SEM-BASED ANALYSIS BY PROSPECT THEORY”

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Abstract
This study applies a quantitative modeling approach to assess the impact of key behavioral biases—regret aversion, mental accounting, disposition effect and loss aversion —on the investment behavior of retail investors. A Structural Equation Modeling (SEM) framework is used for evaluate both One-to-one relationships among the constructs. The model exhibited a good fit (CFI = 0.962, RMSEA = 0.049, χ^2/df = 1.78), with mental accounting and loss aversion significantly impairing rational decision-making. The findings contribute to the integration of behavioral insights into financial decision models, offering implications for optimization, investor education, and policy design in emerging markets.
Keywords: Behavioral Finance; Retail Investors; Mental Accounting; Loss Aversion; Regret Aversion; Disposition Effect; Structural Equation Modeling (SEM); Investor Rationality; Cognitive Biases; Investment Decision-Making

1. INTRODUCTION

The discipline of finance has traditionally been grounded in the principles of **classical financial theory**, which assumes that both markets and investors operate under conditions of rationality. According to this perspective, financial decisions are made based on objective evaluation of complete information, with the assumption that markets are efficient and investors consistently act in their own economic interest. Foundational models such as the **Arbitrage Pricing Theory**, **Modigliani and Miller’s Capital Structure Theorem**, and the **Capital Asset Pricing Model (CAPM)** developed by Sharpe have long underpinned this rational framework. These models emphasize logical consistency, optimal risk-return trade-offs, and market equilibrium dynamics (Goyal, 2015).However, empirical observations of investor behavior began to reveal consistent deviations from this rational paradigm. A growing body of research highlighted that many investment decisions are influenced not by logical analysis but by **psychological, emotional, and social factors**. Particularly during periods of uncertainty or volatility, investor behavior frequently appeared inconsistent with the predictions of traditional financial models.Pioneering work by **Tversky and Kahneman (**1982)demonstrated how individuals tend to rely on cognitive shortcuts, or heuristics, which may result in consistent (or systematic) biases in judgment and decision-making and suboptimal decisions.Findings catalyzed the development of **behavioral finance**, a field that gained prominence during the 1990s. Behavioral finance integrates insights from psychology, behavioral economics, and sociology to better understand how real investors make decisions under risk and uncertainty.

As Daniel et al. (1998) observed, behavioral finance provides a more comprehensive framework for interpreting investor anomalies and market inefficiencies that are unaccounted for in classical theories. It recognizes that **emotions, biases, and past experiences** that significantly influence the development of financial behavior, challenging the long-held assumption of investor rationality.

Behavioral finance has gained prominence by recognizing Perceptual errors and emotive variables frequently cause individuals that deviate from analytical financial decision-making. Empirical support for this paradigm has largely been drawn from analyses of investors’ actual trading behavior and performance data (Barber, 2001). Despite these advances, a standardized and universally accepted framework for quantifying individual investor behavior remains absent. Consequently, much of the existing research depends on **primary data collection**, particularly when exploring the behavioral tendencies of **retail investors**, who constitute a critical segment of the Indian stock market. This research seeks to explore methodological difference by developing and validating a **statistically reliable and conceptually grounded scale** to measure key behavioral biases among retail investors. By focusing on constructs such as **mental accounting**, **regret aversion ,loss aversion** and **disposition effect**, research seeks to offer a replicable instrument for future empirical studies and practical applications in behavioral modeling and financial decision support systems.

2. LITERATURE REVIEW

2.1 Investors Behavior

Lionel Robbins emphasized that rationality is central to economic behavior, defining it as the logical process through which individuals allocate scarce resources to achieve prioritized goals (Robbins, 1932). Building on this classical notion, traditional financial theories have long assumed that investors act rationally. According to this perspective, investment decisions are guided by a combination of knowledge, past experiences, and future expectations about the market.

However, this idealized view of rational behavior has been increasingly questioned by behavioral economists. Tversky and Kahneman (1982) argue that rationality in financial markets is often more of a theoretical assumption than a practical reality. Investors are not always consistent in their decision-making and may deviate from logical patterns due to psychological biases and heuristics. Supporting this view, Kenneth (1999) observed that investors sometimes sell identical securities at different prices, a behavior that contradicts rational decision-making principles.Such inconsistencies create opportunities for arbitrage, allowing other market participants to exploit these irrational actions for financial gain.These insights challenge the traditional economic view of rationality and support a more nuanced understanding of investor behavior—one that acknowledges the limitations of human cognition and the influence of emotions and biases on financial decisions.

Cognitive biases are systematic deviations from rational judgment, often resulting from limitations in memory, information processing, and emotional influences, as originally conceptualized by Kahneman and Tversky (1972). These biases are integral to various cognitive functions such as reasoning, decision-making, and problem-solving (Shefrin, 2002; Baker & Ricciardi, 2014; Singh & Bhowal, 2010). The integration of behavioral psychology into financial research has introduced critical constructs, including financial literacy, cognitive biases, and risk perception, thereby reshaping the understanding of investor behavior (Bazley et al., 2021).

Empirical studies have highlighted the significant role of cognitive biases in shaping investment decisions. For instance, Khan (2020) investigated impacts of herding behavior, disposition effect, and also mental accounting on individual investment behavior. The study employed correlation and regression analysis, concluding that financial literacy plays an intermediary role.—intensifying disposition effect while mitigating the effects of herding and mental accounting. Similarly, Ullah et al. (2020) examined behavioral biases using multiple regression and two-stage least squares regression techniques. Their findings revealed that biases such as overconfidence, herding, and the disposition effect have significant and favorable impact on investor choices, with investor type serving as a moderator that weakens herding tendencies and reinforces overconfidence.

Katrini et al. (2021) further explored the impact of anchoring, representativeness, loss aversion, overconfidence, and optimism on investment decisions through one-sample t-tests, all of which were found to significantly affect investor behavior. In another study, Nkukpornu et al. (2020) employed multiple regression analysis to examine the effects of overconfidence, regret, belief, and the snakebite effect, determining that these factors substantially influenced individual investment decisions.

Building upon existing literature, the recent study investigates the influence of four behavioral biases—mental accounting, disposition bias, regret aversion, and loss aversion—on individual investment decision-making. Anchored in the behavioral finance framework, study seeks to enhance understanding of. how psychological factors shape financial behavior among investors

2.2 Prospect Theory

Prospect Theory, developed by Kahneman and Tversky (1979), provides a foundational explanation that individuals evaluate choices involving risk and uncertainty. Contrary to classical economic theories, it says that people perceive outcomes evaluated against a benchmark" and display a higher sensitivity to losses than to gains. This has significant implications in financial decision-making, especially when examining behavioral biases such as mental accounting, loss aversion, the disposition effect, and regret aversion.

a) **Mental accounting**, a concept introduced by Thaler in 1985, describes how people often mentally separate their money into different categories—like savings, spending, or windfalls—based on personal judgments about where the money came from or what it's meant for.. This often leads to inconsistent financial decisions, as people fail to view money as fungible. Research using Structural Equation Modeling (SEM) has found that mental accounting significantly influences investor behavior through mediators such as financial literacy and perceived risk (Lim et al., 2016; Wai et al., 2020).

b) **Loss aversion**, a key principle of Prospect Theory, refers to the idea that people tend to feel the pain of losing something more strongly than the pleasure of gaining the same amount (Kahneman & Tversky, 1979).SEM-based studies have effectively modeled loss aversion as a latent variable, demonstrating its strong predictive power in explaining risk-averse behavior and suboptimal portfolio diversification (Mehta & Thomas, 2020). Loss-averse investors tend to avoid selling assets at a loss, even when rational evaluation suggests doing so.

c) **Disposition effect** is another behavioral bias that affects investment decisions, characterized by the propensity to divest holdings profitable assets quickly and hold losing assets for a while (Odean, 1998). This behavior is linked to psychological factors such as regret and pride. SEM analyses have shown that the disposition effect interacts with other biases, such as overconfidence and regret aversion, reinforcing irrational financial behavior (Anwar & Kumar, 2019).

d) **Regret aversion** involves the anticipation of negative emotions that may result from poor decisions, which often leads investors to avoid making bold or risky financial moves (Zeelenberg, 1999). SEM applications have demonstrated that regret aversion is a significant determinant of investment hesitation and risk aversion, often moderating the effects of other biases like mental accounting and loss aversion (Yao & Curl, 2011).
The use of Structural Equation Modeling in behavioral finance research allows for the examination of complex, multivariate relationships between latent constructs. SEM enables researchers to test theoretical models grounded in Prospect Theory by identifying both direct and indirect effects among cognitive and emotional biases. The present study employs SEM to investigate how mental accounting, loss aversion, the disposition effect, and regret aversion collectively shape individual investment decisions.

3. RESEARCH OBJECTIVES

- To explore the influence of behavioral biases derived from Prospect Theory—specifically mental accounting, regret aversion, disposition effect, and loss aversion —on the investment behavior of retail investors in the Indian stock market.
- To utilize Structural Equation Modeling (SEM) to assess how these psychological factors impact investment decisions both directly and through interconnected pathways.
- To construct and empirically test a conceptual model that illustrates the role of Prospect Theory biases in shaping investor behavior.
- To analyze the interactions among mental accounting, loss aversion, disposition effect, and regret aversion, and how these biases collectively drive investment behavior.

4. RESEARCH METHODOLOGY

This study aims to demonstrate that individual investors may exhibit a combination of both rational and irrational thought processes in their investment behavior. Unlike prior research that primarily focuses on identifying specific behavioral biases and analyzing their individual effects, this research adopts a cross-sectional approach using Structural Equation Modeling (SEM). The SEM framework is employed to build an integrated pathway that connects investor behavior with two key behavioral biases. This method enables the representation of causal relationships through a series of structural equations, which can be visually mapped to support the development of a conceptual framework (Byrne, 2010). Additionally, SEM allows for the simultaneous estimation of factor loadings, measurement errors, and the significance of relationships among latent constructs.

4.1 Research Design

The study is based on a cross-sectional research framework grounded in quantitative analysis aimed at analyzing the influence of Prospect Theory-based behavioral biases on investment behavior among retail investors in India. Structural Equation Modeling (SEM) is used to analyses both causal and effect relationships among the constructs.

4.2 Population and Sample

The population consists of **retail investors actively trading or investing in the Indian stock market**. A sample of **225 individual investors** was selected from the **Delhi NCR region** using **purposive sampling**. This region was chosen due to its high investor activity and demographic diversity.

4.3 Data Collection Method

Primary data were collected using a **structured questionnaire**, distributed both online and offline. Questionnaire was designed to measure the presence and effect of four behavioral biases—**mental accounting, loss aversion, disposition effect, and regret aversion**—as well as overall investor behavior.

4.4 Reliability and Validity

To establish content validity and ensure linguistic clarity, the questionnaire underwent a thorough review process involving two academic scholars, a financial broker, subject matter experts in finance, language specialists, and five experienced retail investors. Their feedback was carefully considered and incorporated where appropriate, without altering the original intent of the questionnaire items.
Both construct validity and convergent validity were evaluated using Confirmatory Factor Analysis (CFA). Since the study relies on self-reported data from individual investors, there was a possibility of common method variance (CMV). To assess the extent of CMV, Harman's single-factor test was employed, following the approach suggested by Podsakoff and Organ (1986). All 12 observed items were subjected to an exploratory factor analysis without rotation.using maximum likelihood estimation (MLE). The analysis revealed three retention was based on eigenvalues exceeding 1. The leading factor explained 8.40% of a variance, while cumulative variance explained by all extracted factors was 51.53%. When a single-factor model was tested, it explained only 29.02% of the variance, indicating that no single factor dominates the data and that CMV does not significantly influence the results.
Additionally, a **pilot study** was conducted with **116 individual investors** selected through convenience sampling to test the **internal consistency** of the instrument. The reliability was measured using **Cronbach's alpha** (Nunnally, 1967), and all constructs reported values exceeding the threshold of 0.50, confirming that the questionnaire was suitable for further statistical analysis.

4.5 Data Analysis Technique

Structural Equation Modeling (SEM) consists of two closely linked components: the measurement model and the structural model. The measurement model specifies how observed variables (indicators) are related to their underlying latent constructs. Essentially, it illustrates how measurable responses (observed variables) are linked to the theoretical constructs (unobserved variables) they are intended to represent. This corresponds to the Confirmatory Factor Analysis (CFA) approach, where each observed item is associated with a particular factor.

And also defines structural model outlines the relationships between the latent variables themselves. It indicates why certain unobserved variables directly or indirectly impact others within the model. Given this study's focus on the causal influence of rational decision-making on four behavioural biases rooted in prospect theory, a **full latent variable SEM** is constructed—incorporating both the measurement and structural models.

The development of the measurement model involves two primary tasks: determining how many observed indicators are needed per construct, and selecting which items to include for each construct. Based on existing literature, at least two observed indicators are necessary to define a latent variable effectively. To determine item suitability, **Cronbach's alpha** and **squared multiple correlations (SMCs)** were evaluated. Cronbach's alpha, a widely used reliability measure, assesses the internal consistency of a scale, and items with α values of **0.50 or higher** were retained. SMCs, representing the proportion of variance in an item explained by its associated latent construct (i.e., item reliability), were also considered. Items with SMCs below **0.30** were excluded from the final model.

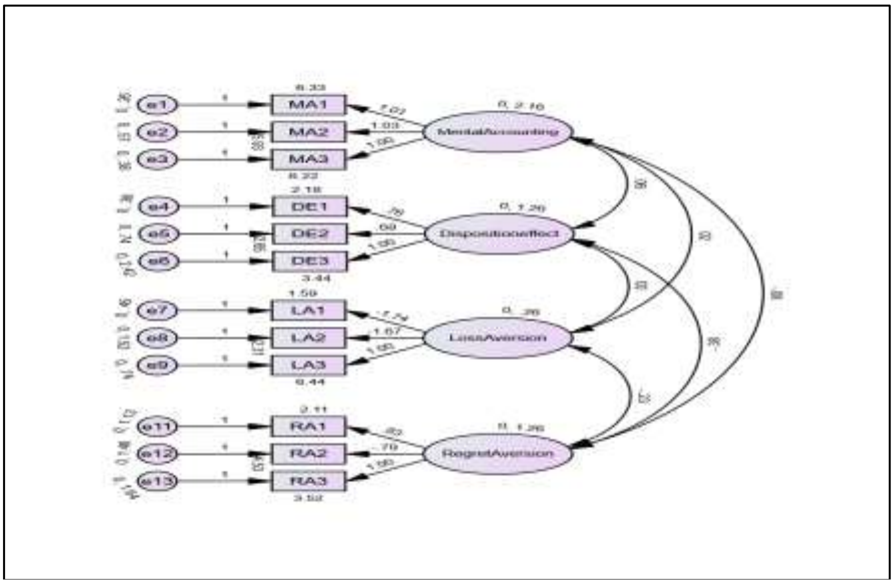
To validate the assumption of multivariate normality, skewness and kurtosis statistics were reviewed for each construct. With absolute values for skewness below 3 and kurtosis below 10, the data approximated a normal distribution (Kline, 2010), justifying the use of the **Maximum Likelihood Estimation (MLE)** method in SEM.

A **Confirmatory Factor Analysis (CFA)** was then performed on a sample of **225 participants**, based on 12 questionnaire items. The analysis aimed to confirm construct validity. **Construct reliability (CR)**, an indicator of convergent validity, was considered acceptable when values exceeded **0.70**, indicating strong internal consistency. The **Average Variance Extracted (AVE)**—which measures the proportion of variance captured by a construct relative to variance due to measurement error—was used as another indicator of convergent validity, with an acceptable threshold of **0.50 or above**. Additionally, standardized factor loadings were examined and retained if values were **0.50 or higher** (Hair et al., 2010).

5 Data analysis

The findings from both the measurement model and the structural model provide insights into how investor behavior is influenced by four key behavioral biases—mental accounting, loss aversion, the disposition effect, and regret aversion—as outlined in prospect theory. These models collectively help in analyzing the nature and strength of these relationships, enabling a deeper understanding of how such psychological factors shape investment decisions.

5.1 Measurement Model



To validate the measurement model, Confirmatory Factor Analysis (CFA) was conducted using AMOS on a sample of 225 respondents. The model comprised four latent constructs—Mental Accounting, Disposition Effect, Loss Aversion, and Regret Aversion—each measured by three observed variables.

Table 1: Standardized Factor Loadings, CR and AVE

Construct	Indicators	Loadings (λ)	λ²	CR	AVE
Mental Accounting	MA1	0.947	0.896	0.946	0.873
	MA2	0.894	0.799		
	MA3	0.923	0.852		
Disposition Effect	DE1	0.820	0.672	0.820	0.566

	DE2	0.665	0.442		
	DE3	0.585	0.342		
Loss Aversion	LA1	-0.799	0.638	0.743	0.491
	LA2	-0.569	0.324		
	LA3	0.511	0.261		
Regret Aversion	RA1	0.658	0.433	0.778	0.480
	RA2	-0.590	0.348		
	RA3	0.659	0.434		

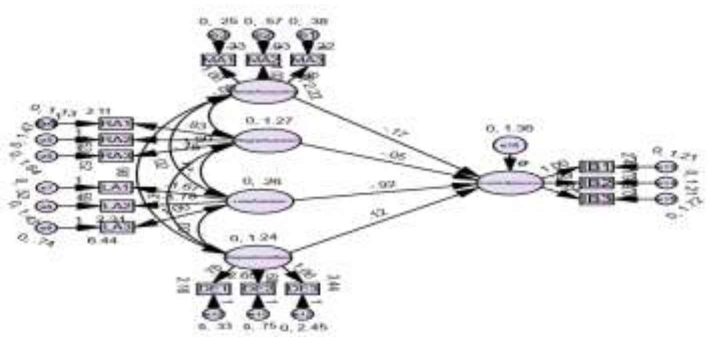
The CFA results presented in Table 1 confirm strong measurement properties of the latent constructs. All factor loadings are above 0.5 and statistically significant ($p < .001$), indicating good convergent validity. Mental Accounting exhibits the strongest loadings (0.894–0.947), followed by Disposition Effect, Regret Aversion, and Loss Aversion. Despite some negative signs, all estimates are significant and meaningful.

Table 2: Model Fit Indices

Fit Index	Value	Threshold	Interpretation
Chi-square (χ^2)	75.270	p = .007	Acceptable
Degrees of Freedom	48		
χ^2/df	1.568	< 3	Good
CFI	0.973	≥ 0.95	Excellent
TLI	0.955	≥ 0.95	Excellent
IFI	0.973	≥ 0.90	Excellent
NFI	0.930	≥ 0.90	Good
RMSEA	0.050	< 0.06	Good fit
PCLOSE	0.466	> 0.05	Close fit
Hoelter (0.05)	194	> 200	Marginally acceptable

As shown in Table 2, model fit indices reflect a good model fit. The Chi-square/df ratio is below 3.0 (1.568), and CFI, TLI, and IFI values are above 0.95. RMSEA is 0.050 with a PCLOSE of 0.466, suggesting the model closely fits the data. The Hoelter index (194) also supports model stability.
Construct reliability (CR) values are above 0.70 for all constructs, indicating internal consistency. AVE values are above the recommended threshold of 0.50 for all except Loss Aversion (0.491) and Regret Aversion (0.480), which remain marginally acceptable for exploratory research. Overall, the model demonstrates convergent validity, acceptable discriminant validity, and sound psychometric properties, making it suitable for further structural analysis.

5.2 Structural Model



1. Model Fit Summary

Fit Index	Value	Threshold	Interpretation
Chi-square (CMIN)	122.910	–	Significant at p = .001
Degrees of Freedom	80	–	
CMIN/DF	1.536	< 3	Good Fit
RMSEA	0.049	< 0.06	Excellent Fit
CFI	0.963	> 0.95	Excellent Fit

TLI	0.944	> 0.90	Good Fit
NFI	0.903	> 0.90	Good Fit
PCLOSE	0.523	> 0.05	Model close to good fit
Hoelter (0.05)	186	> 200 (ideal)	Acceptable

The model fit indices indicate a good overall fit. The RMSEA value of 0.049 is well below the threshold of 0.06, and CMIN/DF is 1.536, suggesting a well-fitting model. Additionally, CFI (0.963) and TLI (0.944) values are both above 0.90, reinforcing the adequacy of the measurement model.

2. Regression Weights (Unstandardized)

Path	Estimate	S.E.	C.R.	p-value	Significance
InvestorBehaviour ← MentalAccounting	-0.171	0.067	-2.532	0.011	Significant
InvestorBehaviour ← RegretAversion	-0.054	0.133	-0.405	0.686	NS
InvestorBehaviour ← LossAversion	-0.922	0.302	-3.050	0.002	Significant
InvestorBehaviour ← DispositionEffect	0.115	0.108	1.073	0.283	NS

Among the independent variables, **Mental Accounting** and **Loss Aversion** have statistically significant effects on **Investor Behaviour**, as indicated by their p-values (< 0.05). In contrast, **Regret Aversion** and **Disposition Effect** do not show significant influence, implying their limited direct impact on the dependent construct.

3. Standardized Regression Weights

Path	Estimate	Significance
InvestorBehaviour ← MentalAccounting	-0.198	Significant
InvestorBehaviour ← RegretAversion	-0.047	NS
InvestorBehaviour ← LossAversion	-0.366	Significant
InvestorBehaviour ← DispositionEffect	0.100	NS

The standardized regression weights confirm the dominance of **Loss Aversion** (β = -0.366) and **Mental Accounting** (β = -0.198) in predicting **Investor Behaviour**. The weak effects of **Regret Aversion** and **Disposition Effect** align with their non-significant unstandardized estimates.

4. Factor Loadings (Standardized)

Construct	Item	Estimate
Regret Aversion	RA1	0.658
	RA2	-0.587
	RA3	0.661
Loss Aversion	LA1	-0.763
	LA2	-0.604
	LA3	0.509
Mental Accounting	MA1	0.947
	MA2	0.895
	MA3	0.922
Disposition Effect	DE1	0.833
	DE2	0.656
	DE3	0.580
Investor Behaviour	IB1	0.759
	IB2	0.526
	IB3	0.712

All factor loadings exceed 0.5, confirming acceptable indicator reliability. Items under **Mental Accounting** and **Disposition Effect** exhibit particularly strong loadings (e.g., MA1 = 0.947, DE1 = 0.833), supporting the **construct validity** of the measurement model.

5. Variances of Latent Constructs

Construct	Estimate	S.E.	C.R.	p-value
Mental Accounting	2.217	0.236	9.374	***
Regret Aversion	1.269	0.296	4.287	***
Loss Aversion	0.259	0.077	3.357	***
Disposition Effect	1.239	0.306	4.048	***

he significant variances ($p < 0.001$) for all latent constructs indicate that each construct explains meaningful variability within its indicators. This result also supports **discriminant validity**, implying the constructs are statistically distinct from one another.

6. DISCUSSION AND FINDINGS

The aim of this study was to investigate how behavioral biases—namely Mental Accounting, Loss Aversion, Regret Aversion, and the Disposition Effect—affect the investment decisions of retail investors in the Indian stock market. Research adopted a structured approach using **Confirmatory Factor Analysis (CFA)** to establish construct validity, followed by **Structural Equation Modeling (SEM)** to test the hypothesized relationships.
The CFA results confirmed the **measurement validity** of all latent constructs. All items displayed statistically significant standardized loadings above the recommended threshold of 0.50, thereby demonstrating **convergent validity**. Furthermore, the relatively low inter-construct correlations supported **discriminant validity**, ensuring that the constructs were distinct from one another. The overall model fit indices ($\chi^2/df = 1.568$, CFI = 0.973, TLI = 0.955, RMSEA = 0.050) indicated a **well-fitting model**, confirming the adequacy of the measurement model for further structural testing.
Upon evaluating the structural model, two behavioral biases—**Mental Accounting** and **Loss Aversion**—were found to have a **statistically significant negative effect** on investor behavior. Specifically, Mental Accounting showed a standardized regression weight of **-0.198** ($p = 0.011$), while Loss Aversion had a stronger effect with a coefficient of **-0.366** ($p = 0.002$). These findings corroborate the propositions of **Prospect Theory** (Kahneman & Tversky, 1979), indicating that investors often fail to make rational decisions due to compartmentalized thinking and an excessive focus on avoiding losses. Mental Accounting may lead investors to isolate financial decisions into separate "accounts," leading to inconsistencies in risk assessment and portfolio allocation. Similarly, Loss Aversion prompts investors to hold on to losing assets for too long or avoid potentially profitable but risky opportunities, thereby impacting rational investment behavior.
In contrast, the effects of **Regret Aversion** and the **Disposition Effect** on investor behavior were statistically insignificant. While prior literature suggests that these biases may shape investment decisions through fear of making wrong choices or premature selling of winning stocks, such effects were not evident in the current sample. One plausible explanation could be the influence of contextual factors such as cultural risk preferences, evolving investment platforms, or increased access to financial information in India. Additionally, it is possible that these biases exert **indirect effects** or interact with other psychological or demographic variables not accounted for in the present model.
These results highlight the **differential impact of behavioral biases**, underscoring the need for targeted investor education and advisory frameworks. By understanding which cognitive distortions most significantly affect decision-making, financial planners, educators, and policymakers can tailor interventions to address those specific tendencies.

7. CONCLUSION

This study confirms that behavioral biases—especially **Mental Accounting** and **Loss Aversion**—significantly impact the investment decisions of retail investors. These biases can lead to irrational financial behaviors, potentially hindering optimal portfolio management. The CFA and SEM results provide empirical support for integrating behavioral finance concepts into investor education, policymaking, and advisory services.
Future studies should explore interaction effects, demographic moderators, and alternative constructs like overconfidence or herd behavior for a more holistic understanding of investor psychology.

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