“Impact of behavioral biases on investment behavior: Mediating role of neuroticism among Indian retail investors”

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IMPACT OF BEHAVIORAL BIASES ON INVESTMENT BEHAVIOR: MEDIATING ROLE OF NEUROTICISM AMONG INDIAN RETAIL INVESTORS

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Abstract

Behavioral theories, rooted in sociological and psychological models, offer intriguing descriptions and explanations of market anomalies and inefficiencies. India is often described as one of the fastest-growing economies globally. The present article explores the role of nine behavioral biases in investment behavior, particularly by addressing the mediating effect of neuroticism among Indian investors. The research framework was developed by an in-depth literature analysis; hypotheses were tested experimentally using SPLS (smart partial least squares) and SEM (structural equation modeling) on a sample of 450 participants from October 1, 2024 to December 30, 2025, and a structured questionnaire was utilized to acquire data from retail investors. Anchoring $\beta = 0.267$, hindsight $\beta = 0.088$, mental accounting $\beta = 0.249$, and overconfidence $\beta = 0.164$ display a noticeably positive impact on investment behavior. Conversely, self-attribution $\beta = -0.283$ shows a significantly adverse impact. However, the disposition effect, emotional bias, herding behavior, and representativeness appear to exert an insignificant impact on investment behavior. The neuroticism trait $\beta = 0.157$ has a significantly positive impact on investment behavior. The findings show that anchoring $\beta = -0.023$, disposition effect $\beta = 0.030$, emotional bias $\beta = 0.023$, herding $\beta = 0.032$, mental accounting $\beta = -0.019$, and overconfidence $\beta = -0.031$ in behavioral finance significantly impact investment behavior indirectly through neuroticism. This model explains 31.1% of the variance in biases; hence, it enhances the mediating role of neuroticism in shaping investment behavior.

Keywords behavioral finance, behavioral biases, neuroticism, investment behavior, retail investors

JEL Classification G41, D91, G11, D53

INTRODUCTION

Retail investors' active participation has served as a crucial factor for promoting favorable trends in the stock market. Notably, the total number of Demat accounts has been remarkable, from 4 crore in 2020 to 13.6 crore in 2025, with new investors interested in participating in the stock market during this timeframe. Statistics from the Bombay Stock Exchange (BSE) show that regions such as Jammu and Kashmir, Chandigarh, and Delhi possess a rising number of active investors.

In reality, some investors achieve returns that surpass market norms, and it appears that most investors do. After all, stock prices are inconsistent with a random walk model. Nevertheless, a variety of empirical outcomes have shown certain abnormalities and paradoxes in financial events such as financial crises and internet bubbles (Shiller, 2015; Wong, 2021), particularly concerning emerging markets where traditional theories fail to provide adequate justifications. Furthermore, existing research primarily underlines cultural individualism and so-

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phisticated financial markets, alongside a notable lack of studies examining individual behavior in financial markets within the Indian context, according to Akhtar and Das (2019).

Recent studies often address singular biases or limited subsets, with personality traits being examined for two or three biases. An in-depth understanding of how neuroticism interplays in shaping the expressions of this extensive spectrum of biases is lacking; however, this gap signifies the need for more extensive empirical and theoretical models that incorporate both personality traits and biases within investment behavior.

1. LITERATURE REVIEW AND HYPOTHESES

As a result, emotional and psychological heuristics influence human preferences and decisions, negotiating complicated relationships throughout the process of decision-making, and may substantially improve the capacity to make decisions, mitigate errors in decision-making, and elevate overall performance. Behavioral finance helps us understand how investors act by giving us useful information about psychological and behavioral variables that affect each one's way of making decisions (Khan & Mubarak, 2022; Ritter, 2003). Ahmad (2024) and Badola et al. (2024) demonstrate that individuals frequently rely on cognitive shortcuts to mitigate the risk of losses in unpredictable scenarios, which can result in judgment errors. Consequently, individuals could end up making irrational decisions.

In several instances, investors' forecasts are based on the initial data, which offer modifications that contribute to a compelling view, an occurrence commonly referred to as anchoring bias (Tversky & Kahneman, 1974). Shiller (2015) examines that investors often place significant value on the prices they have most recently recalled; in addition, they may position themselves in relation to the closest benchmark of a noticeable index, like the Dow Jones. Market participants exhibit anchoring bias (Cen et al., 2013). Anderson and Zastawniak (2017) noticed that investors who were attracted to glamour stocks tended to rely on the initially higher P/E ratio, had trouble with accurately assessing the likelihood of market fluctuations, and therefore found themselves constantly astonished.

Shefrin and Statman (1985) noted that investors tend to dispose of appreciating securities promptly, alongside holding onto diminishing ones for an extended period. Investors tend to favor underperformers over outperformers (Odean, 1998). Individuals exhibiting the disposition effect tend to recognize gains rather than financial losses. Emotional biases arise when individuals overestimate their feelings of regret that relate to suboptimal decisions, especially when weighing alternative options that probably serve better; this bias is commonly known as regret aversion. Kahneman and Tversky asserted in 2013 that the feeling of pain from loss far exceeds the pleasure of gain (Tversky & Kahneman, 1981; Tversky & Kahneman, 1991; Kartini & Nahda, 2021; Aziz et al., 2024). Emotional biases affect investors' investing decisions, as shown by Baker et al. (2019), Gupta Shrivastava (2022), and Bashir and Mehta (2025).

Numerous factors raise the herding behavior observed in the investing choices of managers; it is their inclination to mimic the investment choices of peers (Scharfstein & Stein, 1990). Herding leads investors to behave irrationally (Metawa et al., 2019). The stock market exhibits strong signs of this bias throughout financial crises, including those of 2007–2008 and Covid in 2019–2020. Researchers stated that herding impacts decisions regarding investments (Gupta & Shrivastava, 2022; Gouta & BenMabrouk, 2024).

Overconfidence resulted in too much investment, whereas underconfidence results in underinvestment; nonetheless, moderate overconfidence supported correct investing choices (Pikulina et al., 2017). Individual investors exhibit overconfidence in the stock market while investing (Metawa et al., 2019; Mushinada, 2020; Aziz et al., 2024; Havakhor et al., 2025). Investors with similar attributes envisaged performance outcomes that shape their stock investments (Rasheed et al., 2018; Khan et al., 2021). Additionally, Willows and Richards (2023) discovered that the represen-

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tativeness parameters have a big impact on decisions to buy, while representativeness heuristics and prior profitability serve an essential part in repurchase decisions. Some behavioral models that try to explain the strange returns seen in the real world have incorporated self-attribution bias into traditional learning models, according to financial literature (Chuang & Lee, 2006). Researchers reported that self-attribution is prevalent among investors (Mushinada, 2020).

Previous studies have explored various behavioral biases that impact investors' investment decisions (Yasmin & Ferdaous, 2023; Aziz et al., 2024; Bashir & Mehta, 2025; Yasmin & Sarwar, 2025). The conscientiousness trait exhibited a relationship with the disposition effect and overconfidence, whereas neuroticism demonstrated a link to herding behavior. Authors such as Costa and McCrae (1992), Stone et al. (2001), Statman et al. (2006), Lin (2011), and Gambetti and Giusberti (2012) found that neurotic people exemplify a lack of clarity while investing because of emotional instability and nervousness. Neuroticism shows a notable and positive link with herding and anchoring bias, whereas it exhibits a significant negative link with overconfidence among Indian financial professionals throughout their investing decisions (Baker et al., 2023). Financial advisors frequently note that investors who display characteristics like agreeableness, conscientiousness, openness, extraversion, and neuroticism tend to engage more often in trading (Tauni et al., 2017; Sachdeva & Lehal, 2023). An investor's traits of extraversion and neuroticism have notable positive and negative effects on decisions regarding investments, whereas neuroticism and agreeableness exhibit negative and positive associations with financial literacy (Jain et al., 2023; Akhtar & Das, 2020). However, a dearth of studies still exists despite the essence of personality traits; personality acts as the primary driver of individual behavior, according to Durand et al. (2008). In addition, personality serves an essential part in individuals' investment decisions. Notable influence traits of personality on investment behavior are essential, particularly within the context of emerging nations (Adil et al., 2022; Rajasekar et al., 2023; Mahmood et al., 2024), while fear of missing out serves as a mediator, according to Gupta and Shrivastava (2022). This study focuses on how personality trait (neuroticism) acts as a bridge between the nine behavioral biases, especially within the context of retail investors' behavior while choosing to invest in the stock market of India. To the authors' knowledge, no study has examined personality traits as a mediating factor. Prior studies have taken personality traits as independent variables and studied the direct link to investment behavior. We examine the impact on investment behavior both directly and indirectly. Consequently, we propose that neuroticism serves as a potential mediator that connects the nine behavioral biases to investment behavior. The conceptual framework, as depicted in Figure 1, originates from the literature and hypotheses addressed below.

H1a: Anchoring bias has an impact on personality traits.

H1b: Anchoring bias has an impact on investment behavior.

H1c: The link between anchoring (AB) and investment behavior (RB) is mediated by neuroticism (PT).

H2a: Disposition effect has an impact on personality traits.

H2b: Disposition effect has an impact on investment behavior.

H2c: The link between Disposition effect (DE) and investment behavior (RB) is mediated by neuroticism (PT).

H3a: Emotional biases (EB) have an impact on personality traits (PT).

H3b: Emotional biases (EB) have an impact on investment behavior (RB).

H3c: The link between emotional biases (EB) and investment behavior (RB) is mediated by neuroticism (PT).

H4a: Herding bias has an impact on personality traits.

H4b: Herding bias has an impact on investment behavior.

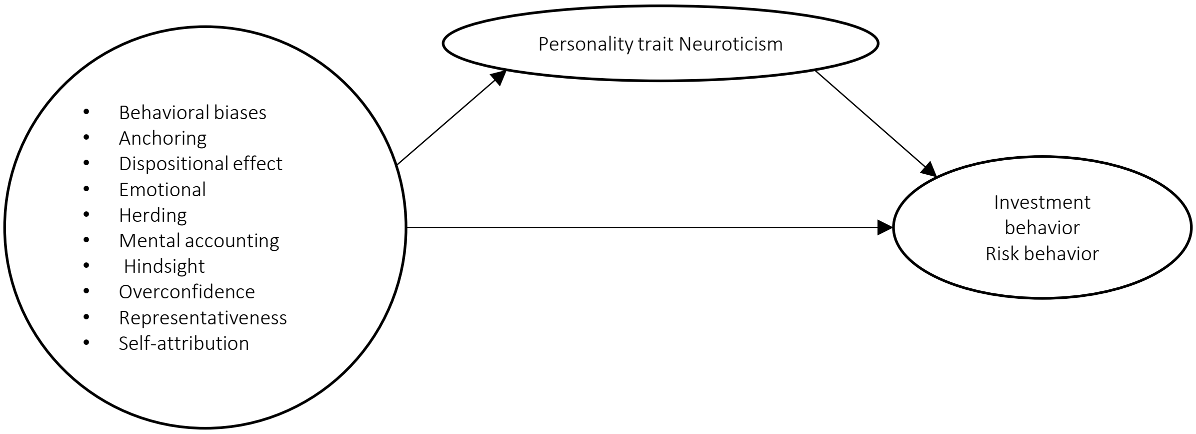

Figure 1. Conceptual framework

H4c: *The link between herding (HB) and investment behavior (RB) is mediated by neuroticism (PT).*

H5a: *Hindsight bias has an impact on personality traits.*

H5b: *Hindsight bias has an impact on investment behavior.*

H5c: *The link between hindsight (HSB) and investment behavior (RB) is mediated by neuroticism (PT).*

H6a: *Mental accounting (MA) has an impact on personality trait (PT).*

H6b: *Mental accounting (MA) has an impact on investment behavior (RB).*

H6c: *The link between mental accounting (MA) and investment behavior (RB) is mediated by neuroticism (PT).*

H7a: *Overconfidence (OC) has an impact on personality traits (PT).*

H7b: *Overconfidence (OC)has an impact on investment behavior (RB).*

H7c: *The link between overconfidence (OC)and investment behavior (RB) is mediated by neuroticism (PT).*

H8a: *Representativeness has an impact on personality traits.*

H8b: *Representativeness has an impact on investment behavior*

H8c: *The link between Representativeness (RP) and investment behavior (RB) is mediated by neuroticism (PT).*

H9a: *Self-attribution has an impact on personality traits.*

H9b: *Self-attribution has an impact on investment behavior.*

H9c: *The link between self-attribution (SA)and investment behavior (RB) is mediated by neuroticism (PT).*

H10: *Personality trait (neuroticism) has an impact on investment behavior.*

2. METHODOLOGY

In this study, data were collected through a questionnaire survey using a quantitative cross-sectional approach. A wide spectrum of studies has been done to find out what kind of behavioral biases are exhibited by retail investors (Wood & Zaichkowsky, 2004; Goo et al., 2010; Lin, 2011; Baker et al., 2019). The objective is to assess investment behavior in relation to risk events (Grable & Lytton, 1999). The personality trait of neuroticism can serve as a mediator when measured (Goldberg, 1993). The survey consists of four separate sections. The initial section of the survey is related to acquiring demographic details, which are on-

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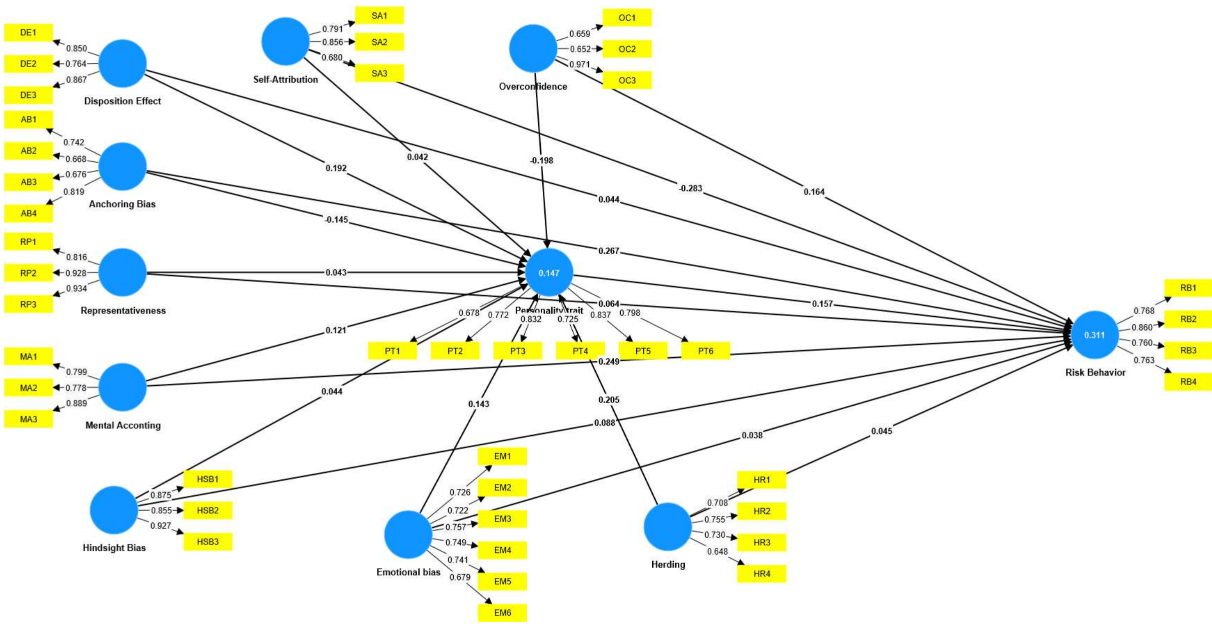

Figure 2. Measurement model

ly used for the sample representative and are appropriate for help in designing the questionnaire. These variables are not the primary focus of the study, so we exclude them from analysis. The second section looks at behavioral biases, comprising 32 questions. All questions are evaluated using a 5-point Likert scale stretching from 1 = strongly disagree to 5 = strongly agree. The third part talks about the personality trait using six items and participants' investment behavior through four items, both being rated on a 5-point Likert scale to rate this behavior.

The same people were asked to answer questions about both dependent and independent variables, along with mediating variables, at the same time for this study. This is important for checking for common method bias (CMB), like Jordan and Troth (2020), Chang et al. (2019), and Taylor (2007), who all conducted similar studies. Harmon's one-factor test is a recognized, accepted method for detecting CMB. Our research results prove that the single factor generated merely 20.28% of the variation, falling far short of the recommended 50% threshold. The graphical representation of the measurement model is in Figure 2.

The study is concentrated on retail investors in India. The survey was carried out throughout multiple cities across northern India, such as Chandigarh, Srinagar, Jammu, Shimla, and Delhi. The structured questionnaires were circulated both in person and via mail to investors in numerous brokerage offices from 1 October 2024 to 30 December 2025. Using non-probability purposive sampling, 515 investors were targeted, and 346 responses were efficiently collected. The sixteen questionnaires were disregarded for having incomplete data, while 330 responses were taken as usable for analysis. We improved our purposive sampling approach through the use of snowball sampling, permitting respondents to recommend even more appropriate investors. A single use of this approach led to a total of 120 responses. Prior studies' efforts have utilized purposive sampling alongside snowball sampling (Sari, 2025; Bashir & Mehta, 2025). Snowball sampling is effective in identifying hidden populations (Johnson, 2014). We ultimately accepted 450 responses as suitable for this research. Following the elimination of responses that were incomplete, quantitative and structural equation methods were employed for further analysis to investigate behavioral biases that make it more difficult for direct observation. In the field of management studies, the PLS (partial least squares) – SEM (structural equation method) is a beneficial way to figure out complicated cause-and-effect models (Gudergan et al., 2008). The pilot questionnaire involved 99 respondents, and their results proved that the questionnaire was both reliable and suitable for the research. G*Power 3.1.9.7 has been used for calculating the sample size (Bashir &Mehta, 2025; Sarstedt et al., 2021; Hair, 2016) and reported a moderate effect size of 0.15 and a test power of 0.95 with ten predictors. Its minimum sample size is 172, while the actual sample size is 450, which is adequate for the study. The author went through pilot testing and decided to keep all items, as each item went above the threshold limit.

3. RESULTS AND DISCUSSION

According to general guidelines, every constructed item should exhibit a factor loading of 0.708 or greater. Still, certain items, which include AB2→0.668, AB3→0.676, EM6→0.679, HR4→0.648, OC1→0.659, OC2→0.652, PT1→0.678, and SA3→0.680, have values underneath this level, with factor loadings above 0.60, identified by Chin et al. (1997), Malhotra et al. (2006), and Hair et al. (2011). As stated by Hair et al. (2013), each item's outer loading ranges from 0.60 to 0.97, which is considered adequate. We scrutinized reliability utilizing (CA) and (CR). However, discriminant and convergent validity procedures were applied to measure validity. Table I Loadings, CR, CA, AVE, VIF values; moreover, Figure 2 provides a visual of the measurement model. In alignment with Hair et al. (2011), AVE should be greater than or equal to for evaluating convergent validity; this threshold suggests that the construct demonstrates a minimum of 50% of the variance noticed among its items. The extracted average variance lies within the acceptable range of 0.506 to 0.800. Cross-loading determines discriminant validity; nevertheless, each of the items has factor loadings that exceed their cross-loadings. Reference Tables 2 and 3 for HTMT and the Fornell and Larsen criteria for discriminant validity. The construct's HTMT remains below the 0.85 threshold; each value is below this limit; therefore, discriminant validity is achieved. Henseler et al. (2015) supported the AVE construct's value of 0.50, matching the diagonal value of Fornell and Larcker (1981). Hair et al. (2006) consider constructions distinct if this value exceeds a comparable construct's correlation. VIF (variance inflation factor) in the presented research is below 5, confirming no multicollinearity.

Table 1. Loadings, CR, CA, AVE, VIF

Constructs	loadings	CR	CA	AVE	VIF
Anchoring	0.742	0.707	0.818	0.531	1.493
	0.668				1.321
	0.676				1.197
	0.819				1.474
Disposition effect	0.850	0.769	0.867	0.686	2.062
	0.764				1.336
	0.867				2.672
Emotional	0.726	0.826	0.872	0.532	1.865
	0.722				1.536
	0.757				1.598
	0.749				1.384
	0.741				2.301
	0.679				1.893
Herding	0.708	0.678	0.803	0.506	1.500
	0.755				2.204
	0.730				1.260
	0.648				1.318
Hindsight	0.875	0.864	0.917	0.786	1.991
	0.855				1.397
	0.927				1.768
Mental accounting	0.799	0.768	0.863	0.678	2.280
	0.778				1.815
	0.889				1.805
Overconfidence	0.659	0.766	0.813	0.601	1.832
	0.652				1.618
	0.971				1.685
Personality trait	0.678	0.868	0.900	0.602	1.426
	0.772				2.200
	0.832				2.688
	0.725				1.099
	0.837				2.327
	0.798				2.851
Risk behavior	0.768	0.796	0.868	0.622	2.216
	0.860				1.567
	0.760				2.520
	0.763				1.915
Representativeness	0.816	0.886	0.923	0.800	1.677
	0.928				1.985
	0.934				1.668
Self-attribution	0.791	0.680	0.821	0.607	2.824
	0.856				1.380
	0.680				1.983

Note: Factor loading → loadings, Composite reliability → CR, Cronbach alpha → CA, Average variance extracted → AVE, variance inflation factor → VIF.

After attaining the measurement model, the next stage is the structural model. Begin with the step of testing the direct relationship. Results are displayed in Table 4; overall results of the hypotheses are positive and significant, except DE → RB (β = 0.044, t = 0.952, p = 0.341), EM → RB (β = 0.038, t = 1.004, p = 0.315), HR → RB (β = 0.04, t = 1.065, p = 0.287), HSB → PT (β = 0.044, t = 0.993,

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Table 2. HTMT ratio

Constructs	Anchoring	Disposition Effect	Emotional	Herding	Hindsight	Mental Accounting	Overconfidence	Personality trait	Representativeness	Self–Attribution
Anchoring Bias (AB)										
Disposition Effect (DE)	0.569									
Emotional bias (EB)	0.202	0.143								
Herding (HB)	0.581	0.567	0.117							
Hindsight Bias (HSB)	0.327	0.390	0.077	0.317						
Mental Accounting (MA)	0.623	0.464	0.127	0.316	0.393					
Overconfidence (OC)	0.448	0.367	0.089	0.358	0.340	0.546				
Personality trait (PT)	0.145	0.304	0.194	0.301	0.144	0.174	0.147			
Representativeness (RP)	0.314	0.292	0.113	0.230	0.125	0.155	0.208	0.095		
Self-attribution (SA)	0.798	0.423	0.115	0.384	0.344	0.688	0.741	0.116	0.227	

p = 0.321), RP → PT (β = 0.046, t = 0.967, p = 0.334), RP → RB (β = 0.067, t = 1.721, p = 0.085), and SA → PT (β = 0.042, t = 0.656, p = 0.512) they are insignificant.

The current research model incorporates the following mediation effect: AN → PT → IB, DE → PT → IB, EM → PT → IB, HR → PT → IB, HSB → PT → IB, MA → PT → IB, OC → PT → IB, RP → PT → IB, and SA → PT → IB. Results of mediation analysis are illustrated in Table 5. The results reveal that the mediating role of personality trait (neuroticism) HSB → PT → RB (β = 0.007, t = 0.923, p = 0.523), RP → PT → RB (β = 0.007, t = 0.930, p = 0.352), SA → PT → RB (β = 0.007, t = 0.639, p = 0.523) was insignificant, while the mediating role is significant for rest of the hypotheses. When direct and indirect effects are significant, the situation is likely that partial mediation takes place (Shankar et al., 2021; Cheung & Lau, 2008). When an independent variable affects a dependent variable exclusively via a mediator, it is called full mediation.

This study examines the personality trait (neuroticism) as a mediator between the biases and investment behavior within Indian retail investors to evaluate the distinctive impact. Research demonstrates that biases impact investment behavior

Table 3. Fornell and Larcker criterion

Constructs	Anchoring	Disposition Effect	Emotional	Herding	Hindsight	Mental Accounting	Overconfidence	Personality trait	Representativeness	Self-Attribution	Anchoring
Anchoring Bias (AB)	0.729										
Disposition Effect (DE)	0.426	0.828									
Emotional bias (EB)	0.150	0.116	0.730								
Herding (HB)	0.409	0.421	0.064	0.711							
Hindsight Bias (HSB)	0.254	0.321	0.060	0.253	0.89						
Mental Accounting (MA)	0.474	0.371	0.109	0.217	0.338	0.823					
Overconfidence (OC)	0.336	0.272	0.083	0.272	0.308	0.417	0.775				
Personality trait (PT)	0.078	0.261	0.163	0.238	0.124	0.143	–0.034	0.776			
Representativeness (RP)	0.382	0.321	0.141	0.269	0.275	0.396	0.269	0.236	0.789		
Self-Attribution (SA)	0.255	0.250	0.080	0.176	0.109	0.145	0.163	0.099	0.195	0.895	
Anchoring Bias (AB)	0.538	0.291	0.078	0.270	0.245	0.491	0.524	0.060	0.139	0.169	0.779

Table 4. Direct effect (H1a to H10)

Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values
H1a. Anchoring Bias → PT	–0.145	–0.145	0.057	2.520	0.012
H1b. Anchoring Bias → RB	0.267	0.262	0.056	4.775	0.000
H2a. Disposition Effect → PT	0.192	0.190	0.052	3.661	0.000
H2b. Disposition Effect → RB	0.044	0.042	0.046	0.952	0.341
H3a. Emotional bias → PT	0.143	0.149	0.042	3.377	0.001
H3b. Emotional bias → RB	0.038	0.043	0.038	1.004	0.315
H4a. Herding → PT	0.205	0.208	0.041	5.007	0.000
H4b. Herding → RB	0.045	0.050	0.043	1.065	0.287
H5a. Hindsight Bias → PT	0.044	0.042	0.045	0.993	0.321
H5b. Hindsight Bias → RB	0.088	0.087	0.043	2.018	0.044
H6a. Mental Accounting → PT	0.121	0.120	0.052	2.302	0.021
H6b. Mental Accounting → RB	0.249	0.246	0.052	4.794	0.000
H7a. Overconfidence → PT	–0.198	–0.197	0.059	3.336	0.001
H7b. Overconfidence → RB	0.164	0.158	0.043	3.830	0.000
H10. PT → RB	0.157	0.155	0.039	3.983	0.000
H8a. Representativeness → PT	0.043	0.046	0.044	0.967	0.334
H8b. Representativeness → RB	0.064	0.067	0.037	1.721	0.085
H9a. Self–Attribution → PT	0.042	0.043	0.064	0.656	0.512
H9b. Self–Attribution → RB	–0.283	–0.265	0.054	5.291	0.000

Note: Original sample → O, Sample mean → M, Standard deviation → STDEV.

Table 5. Specific effect (mediation effect H1c to H9c)

Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values	Mediator Effect
H1c.Anchoring Bias → PT → RB	–0.023	–0.022	0.010	2.173	0.030	PME
H2c.Disposition Effect → PT → RB	0.030	0.029	0.011	2.705	0.007	FME
H3c.Emotional bias → PT → RB	0.023	0.023	0.009	2.512	0.012	FME
H4c.Herding → PT → RB	0.032	0.032	0.010	3.175	0.002	FME
H5c.Hindsight Bias → PT → RB	0.007	0.007	0.008	0.923	0.356	NME
H6c.Mental Accounting → PT → RB	0.019	0.018	0.009	2.094	0.036	PME
H7c.Overconfidence → PT → RB	–0.031	–0.030	0.010	2.961	0.003	PME
H8c.Representativeness → PT → RB	0.007	0.007	0.007	0.930	0.352	NME
H9c.Self–Attribution → PT → RB	0.007	0.007	0.010	0.639	0.523	NME

Note: Full Mediation effect → FME; Partial mediation effect →PME; No mediation effect → NME.

both directly and indirectly through personality traits. Thus, our results are consistent with those of previous studies (Gupta & Shrivastava, 2022; Yasmin & Ferdaous, 2023; Aziz et al., 2024; Bashir & Mehta, 2025; Yasmin & Sarwar, 2025). Gavrilakis and Floros (2022) exhibit that a professional is also influenced by behavioral biases while constructing a portfolio. In our study, behavioral biases significantly impact personality traits such as neuroticism, which in turn significantly impact investment behavior. Several prior studies align with our findings that neuroticism is strongly associated with various behavioral biases exhibited by Indian stock investors, such as Adil et al. (2022), Rajasekar et al. (2023), and Mahmood et al. (2024). Many behavioral biases, which include emotional, dispositional, herding, mental accounting, anchoring, and overconfidence, significantly correlate with the neuroticism trait. The conclusion aligns with earlier research by Baker et al. (2021), Sadi et al. (2011), and Lin (2011). The most important thing we learned from our study is that people with the neuroticism trait tend to have unstable emotions, which can cause depression and anxiety, and make them more willing to take risks and enhance their risk appetite. The outcomes strongly back up the relevance of behavioral finance theories, most notably those pointed out by Daniel Kahneman and Amos Tversky, along-

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side Richard Thaler's mental accounting model. Participants of that kind are inclined to resist external factors when it comes to investment decisions, which creates hardships for working alongside financial advisors and wealth managers. However, these advisors need to formulate an effective strategy to establish trust with their clients. Are they able to do so? They suggest using a stop-loss order, which guides a broker to dispose of a security at a particular price. This helps you make decisions without letting emotions get in the way, and it can help you avoid big losses.

CONCLUSION

This article aims to determine the impact of nine behavioral biases on investment behavior, especially by looking at the mediating role of the neuroticism trait among Indian investors. Findings for the research showed that mental accounting, anchoring, hindsight, mental accounting, and overconfidence have a strong, notable positive impact on investment behavior. Meanwhile, self-attribution shows a negative impact on investment behavior. The disposition effect, emotional factors, herding behavior, and representativeness appear to have an insignificant impact on investment behavior. A trait of personality exerts a significantly positive impact on investment behavior. Our research shows a significantly positive impact of behavioral biases, which include emotional, the disposition effect, herding, and mental accounting, on personality traits. Meanwhile, anchoring and overconfidence have a significantly negative impact on personality traits. The impact of hindsight, representativeness, and self-attribution on personality traits is insignificant. The findings show that anchoring, the disposition effect, emotional, herding, mental accounting, and overconfidence in behavioral finance significantly impact investment behavior indirectly through personality traits. Nevertheless, hindsight, representativeness, and self-attribution exhibit no mediating effect on investment behavior. Moreover, investments made by investors are not consistently grounded in rationality; these can be swayed by various biases, resulting in decisions that cannot be rational. The findings of this study verify this assertion. Consequently, this study enhances the deeper comprehension of how behavioral biases and neuroticism impacted the investment behavior of Indian investors. Our findings allow investors to recognize these biases in their investment behavior and gain a more profound understanding of their impact on decision-making processes. This article provides valuable insights into the literature related to investors' financial behavior during the investment process. It highlights the influence of biases and personality traits on this process and assists in a better understanding of these "your own pockets rules". Behavioral biases impact the investment behavior of investors, ranging from significant to minimal or insignificant effects. This study raises awareness among investors about the impact of behavioral biases on their investment approach in the emerging market of India, recommending avoiding the use of heuristics and other mental shortcuts. As a result, it promotes an in-depth review of all pertinent data throughout the investment decision-making process. The current study provides insights for stock market regulators and policymakers regarding behavioral biases and personality traits that impact the way investors make decisions. We can propose policies and launch educational campaigns to address these behavioral biases. This will promote better stock market performance and improve our comprehension of behavioral finance in a growing economy such as India, where the literature on the existing research is limited.

In future research, it would be beneficial to examine additional factors, such as sociodemographic variables, as these may also impact investment behavior. We only take the neuroticism personality trait as a mediator; more research is required to explore how personality traits, which include agreeableness, conscientiousness, openness, and extraversion, act as mediators between these two. Taking these factors into consideration can improve comprehension of individual investor behavior.

AUTHOR CONTRIBUTIONS

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Investigation: Ishrat Bashir.
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Visualization: Ishrat Bashir, Sushil Mehta.
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