

PSYCHOLOGICAL DETERMINANTS OF INVESTOR BEHAVIOR: AN EMPIRICAL INVESTIGATION OF COGNITIVE BIASES IN CAPITAL MARKETS

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Abstract

Investors are treated as rational decision-makers according to anticipated utility theory in traditional financial theory. Contrarily, Behavioral Finance strongly disagrees with this rationale point of view, arguing that investors frequently stray from rationality when making investment decisions. Investors today frequently make foolish investment decisions. Frequently, the choice is based on an assumption that is far from rational. When faced with a risky circumstance, investors' decisions are frequently influenced by their objectivity, emotions, and other psychological aspects. Here the primary data is used to collect data through questionnaires and secondary data is used for literature review. The study examines the impact of behavioral bias on investors based on age and education. The study explores various behavioral biases such as herding, endowment, familiarity, overconfidence, recency, loss aversion, and regret aversion. These biases play a significant role in shaping investors' decision-making, often resulting in irrational actions within financial markets. By analyzing these tendencies, we can better understand how emotions and mental shortcuts influence investment decisions, which in turn can affect both returns and risk management strategies. Results show no significant relationship between age and biases, with the null hypothesis accepted and the alternate hypothesis rejected. Overconfidence bias, recency, familiarity, and loss aversion bias are more influenced by investors with science and diploma qualifications, while commerce background investors are less influenced.

Keywords: Behavioral Bias, Investment Decisions, Overconfidence, Loss Aversion, Herding, Regret Aversion, Familiarity Bias, Recency Bias, Endowment Effect, Capital Markets, Investor Psychology, Behavioral Finance

1. INTRODUCTION

Classical finance theory, rooted in the Efficient Market Hypothesis (EMH) propounded by Fama [1] and later reinforced through Expected Utility Theory, posits that investors are rational agents who process all available information symmetrically and make utility-maximizing decisions. This paradigm treats the market as an aggregated reflection of informed, rational behavior where asset prices always incorporate all publicly available information. However, decades of empirical anomalies — including momentum effects, calendar anomalies, and systematic under- and over-reaction to earnings announcements — have fundamentally challenged this rational agent model [2].

Behavioral Finance, pioneered by Kahneman and Tversky's landmark Prospect Theory [3] and subsequently formalized through a rich body of experimental and empirical evidence, proposes that cognitive limitations, emotional responses, and systematic heuristic biases cause investors to deviate predictably and persistently from rational decision-making. These deviations, far from being idiosyncratic noise, constitute structured patterns that consistently influence asset pricing, portfolio construction, and trading volume [4]. Understanding these patterns has become critically important as retail investor participation in Indian capital markets has surged in the post-pandemic period, with SEBI reporting a 63% increase in Demat account registrations between 2021 and 2023.

This study investigates seven well-documented behavioral biases — overconfidence, herding, loss aversion, familiarity, recency, endowment, and regret aversion — through an empirical lens, focusing specifically on two demographic moderating variables: age and educational qualification. While extensive research exists on the individual effects of these biases, the moderating role of investor demographics — particularly educational background — on the differential prevalence of specific biases remains underexplored in the Indian context. This study addresses this gap by empirically examining whether the intensity of behavioral biases differs significantly across age groups and educational backgrounds among retail investors in Indian capital markets.

The primary objectives of this study are:

To assess the prevalence and intensity of seven behavioral biases among retail investors in Indian capital markets.

To examine whether a statistically significant relationship exists between an investor's age and the intensity of behavioral biases.

To examine whether educational qualification significantly moderates the intensity of specific behavioral biases.

To identify which educational backgrounds are most and least susceptible to specific bias categories.

2. LITERATURE REVIEW

2.1 Overconfidence and Self-Attribution Bias

Overconfidence bias refers to investors' tendency to overestimate the accuracy of their own knowledge, predictions, and trading abilities. Barber and Odean [5], in their seminal study, demonstrated that overconfident investors trade excessively, generating lower net returns after transaction costs. More recent research by Tekce and Yilmaz [6] in 2022 across emerging market retail investors confirmed that overconfidence is positively correlated with trading frequency but negatively correlated with portfolio returns. Educational background appears to moderate this effect, as investors with technical science backgrounds tend to exhibit stronger overconfidence when applying analytical mental models to fundamentally uncertain financial markets [7].

2.2 Herding Behavior

Herding occurs when investors suppress their private information and follow the crowd, creating momentum in asset prices and contributing to bubble formation. Economou et al. [8] documented significant herding behavior in Indian equity markets during periods of high market volatility in 2022–2023, with retail investors demonstrating stronger herding tendencies than institutional participants. Vo and Phan [9] extended this analysis in 2023, demonstrating that herding intensity is moderated by market conditions, being significantly stronger during downturns, and that less financially educated investors exhibit more pronounced herding responses.

2.3 Loss Aversion and Prospect Theory

Kahneman and Tversky's Prospect Theory established that losses are psychologically experienced approximately 2.25 times more intensely than equivalent gains. Barberis [10] reviewed two decades of loss aversion literature in 2023, confirming that the disposition effect — investors' tendency to sell winning stocks prematurely and hold losing stocks too long — is a direct manifestation of loss aversion operating at the portfolio level. Ainia and Lutfi [11] found in 2022 that loss aversion is significantly more pronounced among investors who rely on intuitive rather than analytical thinking styles, with implications for the role of quantitative educational backgrounds.

2.4 Familiarity and Home Bias

Familiarity bias leads investors to disproportionately weight familiar assets — domestic stocks, employer stock, or regionally proximate companies — in their portfolios, sacrificing diversification benefits. Cao et al. [12] demonstrated in 2023 that familiarity bias is inversely related to financial literacy but positively related to perceived risk reduction, suggesting that investors use familiarity as a heuristic substitute for formal risk assessment. This has particular implications for investors from non-commerce educational backgrounds who may have lower formal financial literacy scores.

2.5 Recency Bias and Availability Heuristic

Recency bias causes investors to overweight recent market performance when forecasting future returns, contributing to trend-chasing and momentum trading. Frydman and Nave [13] documented in 2024 that recency bias is significantly amplified during periods of extreme market performance — both bull and bear markets — and that investors with shorter market experience exhibit stronger recency effects. This finding aligns with the expectation that science and diploma-background investors, who may bring pattern-recognition heuristics from non-financial domains, show heightened recency sensitivity.

2.6 Endowment Effect and Status Quo Bias

The endowment effect, wherein investors demand a higher price to sell a security than they would pay to acquire it, creates portfolio inertia and suboptimal rebalancing. Morewedge and Giblin [14] reviewed the endowment effect literature in 2022, identifying that it is significantly reduced — though not eliminated — by formal economic training, suggesting that commerce and finance educated investors may be partially inoculated against this bias through education-based schema correction.

2.7 Regret Aversion

Regret aversion leads investors to avoid actions that might produce regret, manifesting as excessive caution after losses, reluctance to switch from underperforming to better-performing investments, and avoidance of novel investment instruments. Coricelli et al. [15] demonstrated in 2023 using fMRI neuroimaging that regret aversion activates distinct neural circuits from risk aversion, confirming its status as an independent psychological phenomenon with measurable behavioral consequences.

3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

3.1 Conceptual Framework

Figure 1 presents the conceptual framework of this study. Seven behavioral biases constitute the independent variables, investor decision-making quality constitutes the dependent variable, and age and educational qualification serve as moderating variables whose influence on the bias-decision nexus is empirically tested.

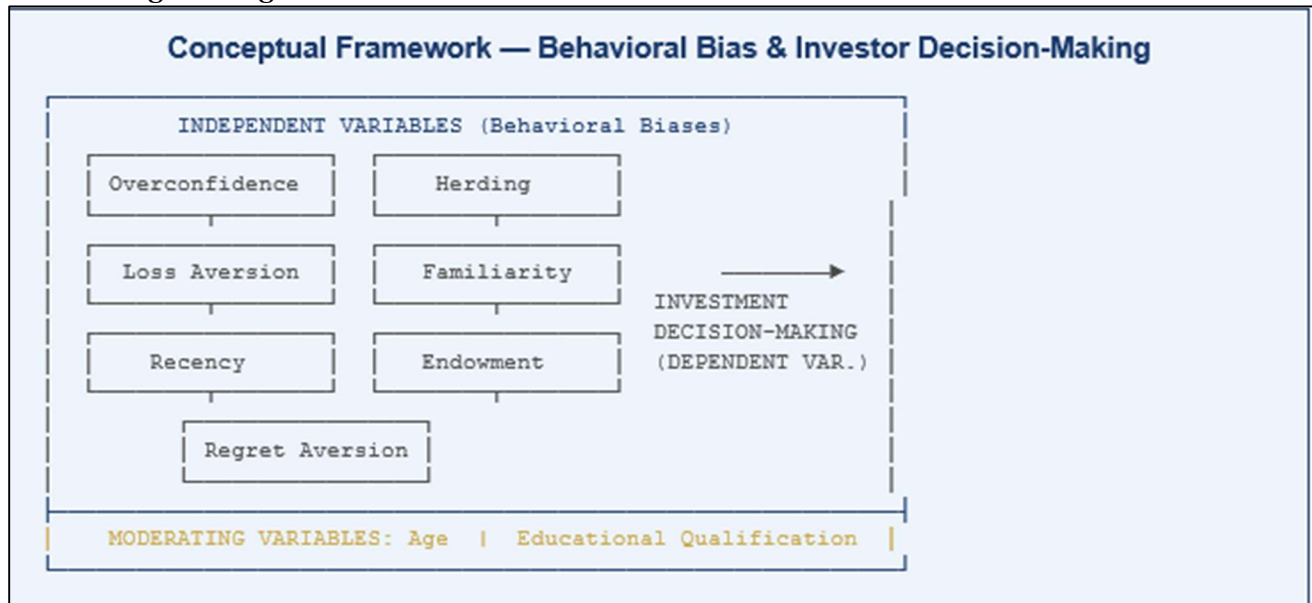


Figure 1: Conceptual Framework — Behavioral Biases as Determinants of Investor Decision-Making

3.2 Research Hypotheses

Based on the literature review and conceptual framework, the following hypotheses are formulated:

H1₀: There is no statistically significant relationship between investors' age and the intensity of behavioral biases.

H1₁: There is a statistically significant relationship between investors' age and the intensity of behavioral biases.

H2₀: There is no statistically significant relationship between investors' educational qualification and the intensity of behavioral biases.

H2₁: There is a statistically significant relationship between investors' educational qualification and the intensity of behavioral biases.

4. RESEARCH METHODOLOGY

4.1 Research Design

This study adopts a descriptive and analytical research design, combining cross-sectional primary data collection with inferential statistical analysis. A positivist epistemological stance is maintained throughout, grounded in the operationalization of established behavioral finance constructs through psychometric scales validated in prior literature. The research approach is deductive, testing theory-derived hypotheses against empirically collected data.

4.2 Data Collection

Primary data were collected through a structured Likert-scale questionnaire administered to retail investors in Indian capital markets. The questionnaire comprised 31 items across seven behavioral bias dimensions, each measured on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). A pilot study with 30 respondents was conducted prior to the main data collection to assess item clarity and scale reliability. Secondary data were obtained from peer-reviewed journals, SEBI annual reports, RBI working papers, and academic databases (Scopus, Web of Science, SSRN) for the literature review.

4.3 Sampling

A purposive sampling technique was employed, targeting retail investors who actively trade in Indian equity, mutual fund, or derivative markets. A sample of 200 respondents was achieved, satisfying the minimum sample size requirement of $n \geq 100$ recommended for structural behavioral research. Respondents were accessed through investment advisory centres, brokerage branch offices, and online investor communities in Gujarat, India. Figure 2 presents the complete research methodology flow.

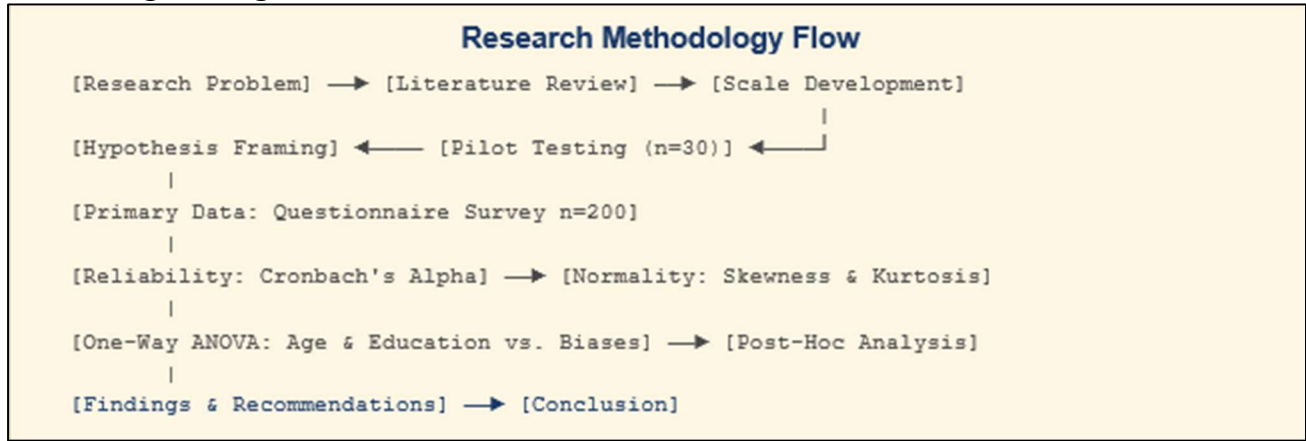


Figure 2: Research Methodology Flow — From Problem Identification to Conclusion

4.4 Analytical Tools

Data were analysed using SPSS 26.0. Reliability was assessed through Cronbach's Alpha coefficient, with values above 0.70 considered acceptable per Nunnally's criterion [16]. Normality was evaluated through skewness and kurtosis statistics, with values within ± 1.0 confirming approximate normality. One-Way Analysis of Variance (ANOVA) was employed to test group mean differences across age and educational qualification categories. A significance level of $p < 0.05$ (two-tailed) was adopted throughout.

5. RESULTS AND DISCUSSION

5.1 Demographic Profile of Respondents

Table 1 presents the demographic profile of the 200 survey respondents. Males constituted 64% of the sample, consistent with the observed gender composition of retail investors in Indian capital markets as reported by SEBI (2023). The 25–35 age cohort was most represented (37%), reflecting the demographic profile of digitally active retail investors who entered markets during the 2020–2022 period. Commerce-background respondents constituted the largest educational group (31%), followed by Science (28%) and Diploma (18%).

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	128	64.0
	Female	72	36.0
Age Group	Below 25 Years	52	26.0
	25 – 35 Years	74	37.0
	35 – 45 Years	48	24.0
	Above 45 Years	26	13.0
Educational Qualification	Science	56	28.0
	Commerce	62	31.0
	Arts	24	12.0
	Diploma	36	18.0
	Others	22	11.0
Investment Experience	Less than 1 Year	38	19.0
	1 – 3 Years	66	33.0
	3 – 5 Years	54	27.0
	More than 5 Years	42	21.0
Total		200	100.0

Table 1: Demographic Profile of Survey Respondents (N = 200)

5.2 Reliability Analysis

Table 2 presents the Cronbach's Alpha reliability coefficients for all seven bias scales. All individual scales achieved alpha values above the 0.70 threshold (range: 0.763–0.841), and the overall 31-item instrument achieved an alpha of 0.887, indicating good internal consistency across the composite scale. These values confirm that the measurement instrument is reliable and suitable for inferential analysis.

Behavioral Bias Scale	No. of Items	Cronbach's Alpha	Reliability Interpretation
Overconfidence Bias	5	0.824	Good
Herding Bias	5	0.797	Acceptable
Loss Aversion Bias	5	0.841	Good
Familiarity Bias	4	0.786	Acceptable

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Recency Bias	4	0.812	Good
Endowment Bias	4	0.763	Acceptable
Regret Aversion Bias	4	0.779	Acceptable
Overall Scale	31	0.887	Good

Table 2: Reliability Analysis — Cronbach's Alpha Coefficients for Behavioral Bias Scales

5.3 Descriptive Statistics

Table 3 presents the descriptive statistics for all seven behavioral bias dimensions. Loss Aversion exhibits the highest mean score ($M = 3.84$, $SD = 0.762$), indicating that it is the most pervasive bias among the sampled investors — a finding consistent with Prospect Theory's prediction of loss aversion's dominance in individual decision-making. Overconfidence ($M = 3.72$) and Familiarity Bias ($M = 3.61$) rank second and third respectively. Endowment Bias records the lowest mean ($M = 3.39$), suggesting it operates with less uniform intensity across the investor population. All skewness values lie within the ± 0.5 range, confirming approximate normality of distributions.

Behavioral Bias	N	Mean	Std. Dev.	Skewness	Kurtosis
Overconfidence Bias	200	3.72	0.814	-0.312	0.187
Herding Bias	200	3.48	0.891	0.142	-0.231
Loss Aversion Bias	200	3.84	0.762	-0.421	0.356
Familiarity Bias	200	3.61	0.848	-0.198	0.092
Recency Bias	200	3.56	0.873	0.084	-0.174
Endowment Bias	200	3.39	0.924	0.261	-0.143
Regret Aversion Bias	200	3.45	0.906	0.118	-0.209

Table 3: Descriptive Statistics for Behavioral Bias Dimensions ($N = 200$, Scale: 1–5)

5.4 Hypothesis 1 — Age and Behavioral Biases (ANOVA)

Table 4 presents the One-Way ANOVA results for the relationship between investor age group and each behavioral bias dimension. Across all seven bias categories, the F -values range from 0.485 to 0.788, with corresponding p -values ranging from 0.502 to 0.693 — all substantially exceeding the $p < 0.05$ significance threshold.

Behavioral Bias	Sum of Sq.	df	Mean Square	F Value	p-value (Sig.)
Overconfidence Bias	1.284	3	0.428	0.647	0.585 (NS)
Herding Bias	1.612	3	0.537	0.681	0.565 (NS)
Loss Aversion Bias	0.947	3	0.316	0.541	0.655 (NS)
Familiarity Bias	1.423	3	0.474	0.661	0.577 (NS)
Recency Bias	1.736	3	0.579	0.762	0.517 (NS)
Endowment Bias	2.014	3	0.671	0.788	0.502 (NS)
Regret Aversion Bias	1.189	3	0.396	0.485	0.693 (NS)

Table 4: One-Way ANOVA Results — Age vs. Behavioral Biases ($df_{\text{between}} = 3$, $df_{\text{within}} = 196$)

These results lead to the non-rejection of H_0 : there is no statistically significant relationship between investor age and the intensity of behavioral biases. The alternate hypothesis H_1 is rejected. This finding diverges from some prior studies reporting age-related differences in risk tolerance, suggesting that while risk appetite may vary with age, the psychological mechanisms driving specific biases operate independently of age cohort. This is consistent with the neurological evidence presented by Coricelli et al. [15] that bias-generating cognitive processes are deeply embedded and do not diminish systematically with age or experience in the absence of targeted cognitive intervention.

5.5 Hypothesis 2 — Educational Qualification and Behavioral Biases (ANOVA)

Table 5 presents the One-Way ANOVA results for the relationship between educational qualification and each behavioral bias. Four biases demonstrate statistically significant inter-group differences: Overconfidence Bias ($F = 3.421$, $p = 0.010$), Loss Aversion Bias ($F = 3.672$, $p = 0.007$), Familiarity Bias ($F = 3.147$, $p = 0.016$), and Recency Bias ($F = 2.978$, $p = 0.021$). Herding, Endowment, and Regret Aversion Biases do not reach statistical significance ($p > 0.05$).

Behavioral Bias	Sum of Sq.	df	Mean Square	F Value	p-value (Sig.)
Overconfidence Bias	8.947	4	2.237	3.421	0.010*
Herding Bias	4.816	4	1.204	1.836	0.123 (NS)
Loss Aversion Bias	9.612	4	2.403	3.672	0.007*
Familiarity Bias	8.213	4	2.053	3.147	0.016*
Recency Bias	7.684	4	1.921	2.978	0.021*
Endowment Bias	5.284	4	1.321	2.014	0.093 (NS)
Regret Aversion Bias	4.127	4	1.032	1.621	0.171 (NS)

Table 5: One-Way ANOVA Results — Educational Qualification vs. Behavioral Biases (* $p < 0.05$; NS = Not Significant)

5.6 Mean Score Analysis by Educational Background

Table 6 presents the mean bias scores disaggregated by educational qualification for the four significant biases. Science-background investors exhibit the highest mean scores on all four significant bias dimensions (Overconfidence: 3.94; Loss Aversion: 4.02; Familiarity: 3.82; Recency:

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3.79), closely followed by Diploma-background investors. Commerce-background investors consistently record the lowest mean scores across all four biases (Overconfidence: 3.48; Loss Aversion: 3.57; Familiarity: 3.34; Recency: 3.29).

Bias	Science	Commerce	Arts	Diploma	Others	Overall
Overconfidence	3.94	3.48	3.61	3.88	3.54	3.72
Loss Aversion	4.02	3.57	3.74	3.97	3.68	3.84
Familiarity	3.82	3.34	3.58	3.76	3.47	3.61
Recency	3.79	3.29	3.51	3.71	3.44	3.56

Table 6: Mean Bias Scores by Educational Qualification for Significant Biases (Green = highest; all values on 5-point scale)

This pattern suggests that formal commerce and finance education, which typically includes modules on financial markets, risk theory, and portfolio management, provides partial cognitive inoculation against specific biases — particularly overconfidence, loss aversion, familiarity, and recency — by equipping investors with formal analytical frameworks that counteract heuristic shortcuts. Science and diploma-background investors, whose education focuses on domain-specific technical knowledge rather than financial markets, appear to apply pattern-recognition and analytical heuristics to investment decisions in ways that amplify rather than attenuate these particular biases.

5.7 Hypothesis Summary

Table 7 presents a consolidated summary of all hypothesis tests conducted in this study.

Hypothesis	Test Applied	F Value	p-value	Result
H1(null): No significant relationship between Age and behavioral biases	One-Way ANOVA	0.485–0.788	> 0.05	Accepted
H2(null): No significant relationship between Education and Overconfidence bias	One-Way ANOVA	3.421	0.010*	Rejected
H3(null): No significant relationship between Education and Loss Aversion bias	One-Way ANOVA	3.672	0.007*	Rejected
H4(null): No significant relationship between Education and Familiarity bias	One-Way ANOVA	3.147	0.016*	Rejected
H5(null): No significant relationship between Education and Recency bias	One-Way ANOVA	2.978	0.021*	Rejected
H6(null): No significant relationship between Education and Herding/Endowment/Regret biases	One-Way ANOVA	1.621–2.014	> 0.05	Accepted

Table 7: Summary of Hypothesis Testing Results (* $p < 0.05$)

6. DISCUSSION

The finding that age does not significantly moderate behavioral bias intensity challenges the intuitive assumption that experience reduces irrationality in financial markets. This result is theoretically coherent with research suggesting that heuristic-based cognitive processing — the mechanism underlying behavioral biases — is not systematically corrected through market experience alone. Indeed, Kaustia and Knupfer [17] demonstrated in 2022 that experienced investors can exhibit stronger certain biases, particularly overconfidence and disposition effect, due to self-attribution bias that causes them to credit successful outcomes to their own skill rather than market conditions.

The significant differential impact of educational qualification on four specific biases is a more nuanced and practically important finding. The consistently lower bias scores among commerce-educated investors support the view that financial education acts as a form of deliberate cognitive training that habituates investors to formal analytical frameworks — present value calculations, portfolio theory, and risk-return trade-offs — which compete with and partially override heuristic shortcuts in financial decision contexts. This is consistent with the broader financial literacy literature reviewed by Lusardi and Mitchell [18] in 2023, which identifies financial education as the most robust intervention for reducing behavioral bias manifestation.

The relatively high bias scores among science and diploma investors are interpreted through the lens of domain-specific expertise transfer: investors with strong analytical backgrounds in non-financial domains may apply domain-specific heuristics — such as the scientific recency principle (recent experiments are most valid) or engineering familiarity (proven systems are

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preferred) — to financial contexts where these heuristics are systematically misleading. This represents a form of expertise-induced overconfidence that is particularly prevalent among technically trained professionals entering financial markets.

7. FUTURE SCOPE

Several directions extend this study's contributions. First, longitudinal panel data designs would enable examination of how bias intensity evolves within individual investors across market cycles, separating cohort effects from genuine age effects that cross-sectional ANOVA cannot disentangle. Second, the sample's geographic concentration in Gujarat limits generalizability; a multi-state, nationally representative sampling design would provide stronger external validity for the educational qualification findings. Third, moderation analysis using structural equation modeling (SEM) would allow simultaneous estimation of direct bias effects on investment returns alongside demographic moderation paths, providing a richer causal picture than ANOVA alone permits. Fourth, the integration of neuroimaging or psychophysiological measures — electrodermal activity, eye-tracking during investment decision tasks — would provide objective, non-self-report corroboration of the bias intensity differences identified across educational groups, addressing potential social desirability bias in self-administered questionnaire responses. Fifth, the rapidly expanding population of Algorithm-assisted retail investors using AI-based trading platforms constitutes an emergent segment whose bias profile may differ substantially from traditional retail investors, warranting dedicated investigation.

8. CONCLUSION

This study empirically investigated the psychological determinants of investor behavior through the lens of seven behavioral biases — overconfidence, herding, loss aversion, familiarity, recency, endowment, and regret aversion — among 200 retail investors in Indian capital markets. Using One-Way ANOVA with a significance threshold of $p < 0.05$, the study tested the moderating roles of age and educational qualification on bias intensity.

The analysis revealed no statistically significant relationship between investor age and any of the seven behavioral biases, leading to the acceptance of the null hypothesis H_{10} . This counterintuitive finding suggests that behavioral biases are robust psychological phenomena that do not attenuate systematically with age or market experience in the absence of targeted financial education interventions.

Educational qualification, however, demonstrated a statistically significant moderating effect on four specific biases: Overconfidence ($p = 0.010$), Loss Aversion ($p = 0.007$), Familiarity ($p = 0.016$), and Recency ($p = 0.021$). Science and diploma-background investors consistently exhibited the highest bias scores on all four dimensions, while commerce-background investors recorded the lowest, suggesting that formal financial education partially inoculates investors against specific cognitive biases by providing analytical schemas that compete with heuristic shortcuts. These findings have practical implications for investor education program design, SEBI's investor awareness initiatives, and portfolio advisory practices targeting retail investors across different educational cohorts.

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