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Role of Investor Biases and Risk in Investment Decision-Making: An Empirical Study

Jaya Jose[1], Dr. Seema Balan[2], Dr. Monika Rana[3]

[1]Research Scholar, Kerala University of Fisheries and Ocean Studies, Kochi, Kerala, India

[2]Assistant professor -Senior grade, Department of Management Studies, Saveetha Engineering College, Thandalam, Chennai, Tamil Nadu, India

[3]Assistant Professor, School of management studies, CGC University, Mohali, Punjab, India

Abstract:

This study investigates how behavioural biases and financial risk propensity shape investment decision-making among stock-market investors in South India. Drawing on behavioural finance and prospect theory, the analysis distinguishes six recurring biases—overconfidence, herding, anchoring, loss aversion, the disposition effect, and representativeness—and positions financial risk propensity as a behavioural mechanism through which these biases influence market decisions. A cross-sectional survey was conducted among 438 active individual investors drawn from Kerala, Tamil Nadu, Karnataka, Telangana, and Andhra Pradesh. The measurement instrument contained 34 scale items and was assessed through confirmatory factor analysis before testing the structural relationships with covariance-based structural equation modelling. Loss aversion emerged as the most pronounced bias, followed by overconfidence and anchoring. The measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity. The structural model showed that overconfidence, herding, anchoring, loss aversion, and representativeness significantly affected financial risk propensity, whereas the disposition effect did not produce an independent effect on risk propensity. Financial risk propensity, in turn, exerted a strong positive influence on investment decision-making. Direct effects from overconfidence, herding, anchoring, loss aversion, and the disposition effect to investment decision-making were significant; representativeness operated primarily through risk propensity. Bootstrapped mediation results confirmed that financial risk propensity partially transmitted the effects of overconfidence, herding, anchoring, and loss aversion and fully transmitted the effect of representativeness. The findings demonstrate that investor decision-making is not adequately explained by bias identification alone: the behavioural consequences of a bias depend materially on how the investor processes financial risk. The study contributes an integrated bias-risk-decision framework for emerging-market retail investors and offers implications for investor education, advisory profiling, brokerage communication, and behavioural risk management.

Keywords: behavioural finance; investor biases; financial risk propensity; investment decision-making; retail investors; structural equation modelling; South India

JEL Classification: G11, G40, G41

1. Research Context and Problem Framing

Retail participation has become an increasingly consequential feature of India's securities market. Digital account opening, app-based brokerage, real-time market information, social-media commentary, and lower transaction costs have reduced the operational barriers that previously separated households from direct equity investing. The Securities and Exchange Board of India's Investor Survey 2025 reported that awareness of stocks and shares had reached 49% of Indian households, while the National Stock Exchange continued to report substantial expansion in registered client accounts across Indian states and union territories. Greater access, however, does not imply that investment choices are fully rational. Retail investors often process uncertainty through cognitive shortcuts, reference points, emotions, social signals, and prior outcomes, creating systematic departures from the assumptions of traditional finance (SEBI, 2026; Tversky & Kahneman, 1974).

Behavioural finance addresses this gap by treating investors as boundedly rational decision makers whose judgments are influenced by psychological tendencies as well as information and expected return. Prospect theory established that individuals evaluate gains and losses relative to reference points and commonly react more strongly to losses than to equivalent gains (Kahneman & Tversky, 1979). Subsequent research documented persistent anomalies such as overconfidence, the disposition effect, herding, anchoring, representativeness, and loss aversion in both developed and emerging markets. These biases can affect security selection, trading frequency, holding periods, reaction to market news, diversification, and willingness to accept financial risk (Barber & Odean, 2001; Odean, 1998; Shefrin & Statman, 1985).

The Indian context is particularly relevant because rapid growth in retail participation has coincided with increased exposure to market information from heterogeneous sources. Evidence from Delhi-NCR found that overconfidence, herding, optimism, and the disposition effect vary with investor demographics and trading sophistication (Prosad et al., 2015). Research from Punjab ranked herding, loss aversion, and overconfidence among the most influential behavioural criteria in equity investment decisions (Jain et al., 2020). More recent Indian studies have continued to show that behavioural tendencies remain important even when financial literacy, investor demographics, and perceived financial risk are incorporated into the analysis (Agarwal et al., 2025; Hans et al., 2026; Raj, 2026).

1.1 Research Gap and Contribution

Three limitations remain evident in the empirical literature. First, many studies examine a narrow subset of biases or treat behavioural bias as a single aggregate construct, reducing the ability to distinguish biases that increase willingness to take risk from those that suppress it. Second, direct bias-to-decision models often overlook the behavioural role of financial risk propensity. Risk propensity is analytically distinct from loss aversion: the former reflects willingness to accept uncertain financial outcomes, whereas the latter reflects asymmetric sensitivity to losses relative to gains (van Dolder & Vandenbroucke, 2024). Third, geographically integrated evidence remains limited in the Indian context. Delhi-NCR and Punjab have received attention, while comparable multi-state evidence from South India remains less developed.

This study addresses these limitations through an integrated framework in which six investor biases are examined simultaneously, financial risk propensity is modelled as an intervening mechanism, and investment decision-making is treated as the principal behavioural outcome. Methodologically, the study moves beyond mean comparisons by validating the measurement model and estimating direct and indirect effects through covariance-based structural equation modelling. The analysis also reports effect sizes, bootstrapped confidence intervals, model fit, multicollinearity diagnostics, common-method checks, and robustness estimates with demographic and trading controls.

1.2 Research Objectives and Questions

Table 1. Research objectives and analytical focus

Objective	Analytical focus
O1	To identify the prevalence and relative intensity of overconfidence, herding, anchoring, loss aversion, disposition effect, and representativeness among stock-market investors in South India.
O2	To examine the influence of the six investor biases on financial risk propensity.
O3	To assess the direct effects of investor biases and financial risk propensity on investment decision-making.
O4	To test whether financial risk propensity mediates the relationship between investor biases and investment decision-making.

The central research question is whether behavioural biases influence investment decisions only as direct psychological tendencies or whether their effects are transmitted through the investor's willingness to accept financial risk. This distinction is important because the same observable bias can have different portfolio consequences depending on risk orientation.

2. Behavioural Finance Lens and Hypothesis Architecture

The theoretical model combines behavioural finance with prospect theory. Behavioural finance explains systematic deviations from rational processing, while prospect theory provides the principal mechanism for understanding reference dependence, asymmetric valuation of gains and losses, and risk-seeking or risk-averse reactions across domains. Financial risk propensity is introduced as a behavioural bridge between cognitive-emotional bias and investment action. In this framework, a bias changes how market information is interpreted; risk propensity captures how that interpretation is converted into willingness to accept uncertain outcomes; and investment decision-making reflects the investor's self-directed buy, sell, hold, allocation, and timing decisions.

2.1 Overconfidence: Perceived Skill and Control

Overconfidence occurs when investors overestimate the precision of their information, forecasting ability, or capacity to outperform the market. It can encourage excessive trading, under-diversification, and greater reliance on personal judgment (Barber & Odean, 2001). Contemporary evidence also indicates that market experience does not necessarily eliminate overconfidence; biased learning can reinforce confidence when investors overweight episodes of past outperformance (Bernile et al., 2025). In investment settings, greater perceived competence can reduce subjective uncertainty and increase willingness to accept risk. Accordingly, overconfidence is expected to raise financial risk propensity and independently intensify self-directed investment action.

H1a: Overconfidence has a positive effect on financial risk propensity.
H2a: Overconfidence has a positive effect on investment decision-making.

2.2 Herding: Social Information and Conformity

Herding describes the tendency to imitate the actions, opinions, or market positions of other investors instead of relying exclusively on private information. Informational cascades can arise when individuals infer that the behaviour of others contains superior information (Bikhchandani et al., 1992). In digital markets, visible trends, influencer commentary, peer groups, and rapid information diffusion can intensify such social cues. Herding may increase willingness to take risk when investors perceive crowd participation as implicit validation of an uncertain trade. Evidence from Indian and other emerging markets continues to associate herding with investment behaviour and risk-related choices (Islam et al., 2024; Mahmood et al., 2024).

H1b: Herding has a positive effect on financial risk propensity.
H2b: Herding has a positive effect on investment decision-making.

2.3 Anchoring: Dependence on Reference Values

Anchoring arises when an investor places disproportionate weight on an initial value, such as a purchase price, recent high, analyst target, index level, or historical return. Subsequent judgments are adjusted insufficiently away from that reference point. Anchoring can distort valuation and delay portfolio revision even when new information is available. Studies of individual investors show that anchoring and adjustment are associated with investment choices, particularly in information-rich environments where multiple numerical cues compete for attention (Mahmood et al., 2024). Because anchors can create a subjective sense of a 'reasonable' entry or exit point, they may influence both willingness to accept risk and the final investment action.

H1c: Anchoring has a significant effect on financial risk propensity.
H2c: Anchoring has a significant effect on investment decision-making.

2.4 Loss Aversion: Asymmetric Sensitivity to Outcomes

Loss aversion refers to the tendency to experience losses more intensely than equivalent gains. It is central to prospect theory and differs conceptually from conventional risk aversion (Kahneman & Tversky, 1979). Recent evidence from large-scale behavioural risk profiling confirms that loss aversion and standard risk-return preferences capture complementary aspects of investor intent (van Dolder & Vandenbroucke, 2024). In portfolio settings, strong loss aversion can suppress entry into volatile assets, delay realization of losses, or produce defensive reallocation. The present model therefore expects loss aversion to reduce financial risk propensity and to restrain active investment decision-making under uncertainty.

H1d: Loss aversion has a negative effect on financial risk propensity.
H2d: Loss aversion has a negative effect on investment decision-making.

2.5 Disposition Effect: Realizing Gains and Retaining Losses

The disposition effect describes the tendency to sell appreciating investments too early while retaining losing positions for too long. It is commonly attributed to reference dependence, regret avoidance, and the desire to convert paper gains into realized success while postponing the psychological recognition of a loss (Odean, 1998; Shefrin & Statman, 1985). Unlike broad risk propensity, the disposition effect is outcome-specific: an investor can be generally willing to accept risk while still resisting the realization of a losing security. It is therefore expected to influence investment decisions directly, whereas its independent relationship with generalized financial risk propensity may be weaker.

H1e: The disposition effect has a significant effect on financial risk propensity.
H2e: The disposition effect has a positive effect on investment decision-making tendencies.

2.6 Representativeness: Pattern Matching and Extrapolation

Representativeness bias occurs when investors judge an asset or market event by its similarity to a familiar pattern and underweight base-rate information. Recent performance, a salient company narrative, or a perceived ‘type’ of winning stock can be treated as representative of future outcomes. This shortcut can lead investors to extrapolate trends and overreact to limited samples of information (Tversky & Kahneman, 1974). Such pattern-based confidence can affect risk willingness even when it does not independently determine the final transaction. Representativeness is therefore expected to influence financial risk propensity and may also exert a direct effect on investment decision-making.

H1f: Representativeness has a positive effect on financial risk propensity.
H2f: Representativeness has a positive effect on investment decision-making.

2.7 Financial Risk Propensity as a Behavioural Mechanism

Financial risk propensity reflects an investor’s willingness to accept uncertain monetary outcomes in pursuit of higher expected returns. It is not equivalent to observed portfolio volatility, because it captures a psychological orientation toward financial uncertainty rather than an ex post risk statistic. Grable and Lytton (1999) demonstrated the relevance of measuring individual financial risk tolerance as a multidimensional construct, and recent behavioural-finance research has shown that prospect, herding, and heuristic dimensions can influence risk propensity, which in turn affects investment decisions (Islam et al., 2024). Accordingly, risk propensity is expected to have a strong positive effect on investment decision-making and to transmit part of the influence of specific behavioural biases.

H3: Financial risk propensity has a positive effect on investment decision-making.

Table 2. Hypothesis architecture

Hypothesis	Structural path	Expected direction
H1a	Overconfidence → Risk propensity	Positive

H1b	Herding → Risk propensity	Positive
H1c	Anchoring → Risk propensity	Significant
H1d	Loss aversion → Risk propensity	Negative
H1e	Disposition effect → Risk propensity	Significant
H1f	Representativeness → Risk propensity	Positive
H2a	Overconfidence → Investment decision-making	Positive
H2b	Herding → Investment decision-making	Positive
H2c	Anchoring → Investment decision-making	Significant
H2d	Loss aversion → Investment decision-making	Negative
H2e	Disposition effect → Investment decision-making	Positive
H2f	Representativeness → Investment decision-making	Positive
H3	Risk propensity → Investment decision-making	Positive

3. Empirical Design

3.1 Population, Screening and Sampling

The target population comprised individual stock-market investors residing in South India who had executed at least one equity transaction during the preceding 12 months. Respondents were required to be 18 years of age or older and to make at least part of their investment decisions independently. Investors whose activity was limited to mandatory retirement products, fixed deposits, or professionally managed pooled funds were not included unless they also traded listed equities directly.

Data were collected between February and May 2026 using a multi-source, quota-assisted purposive sampling strategy. Respondents were approached through brokerage offices, investor education groups, professional networks, and verified online investor communities in Kerala, Tamil Nadu, Karnataka, Telangana, and Andhra Pradesh. Regional quotas were used to avoid concentration in a single metropolitan market. Of 486 returned questionnaires, 31 were removed because of incomplete responses exceeding 10% of scale items, nine failed the stock-investor screening criteria, and eight displayed invariant response patterns. The final analytical sample consisted of 438 investors, representing a usable-response rate of 90.1% among returned questionnaires.

Participation was voluntary and anonymous. The questionnaire did not request demat account numbers, permanent account numbers, broker credentials, exact portfolio values, or personally identifying financial information. Respondents reviewed an informed-consent statement before proceeding. The analytical dataset contained only coded demographic characteristics, investment experience, trading frequency, and scale responses.

3.2 Instrument Development and Construct Measurement

A structured questionnaire was developed from established behavioural-finance constructs and recent investor studies. The initial item pool was reviewed by two finance academics, one behavioural researcher, and two market professionals for construct relevance, clarity, and contextual suitability. A pilot administration with 42 active investors was used to identify ambiguous wording and excessive item similarity. After refinement, the final instrument contained 34 measurement items: four items each for overconfidence, herding, anchoring, loss aversion, disposition effect, and representativeness; five items for financial risk propensity; and five items for investment decision-making. All latent constructs were measured on a seven-point agreement scale from 1 = strongly disagree to 7 = strongly agree.

The bias items were adapted conceptually from the behavioural-finance literature and Indian investor studies (Jain et al., 2020; Prosad et al., 2015; Tversky & Kahneman, 1974). Financial risk propensity items captured willingness to accept short-term volatility, uncertain outcomes, and a higher probability of loss in exchange for superior expected return, consistent with the financial risk-tolerance literature (Grable & Lytton, 1999). Investment decision-making items captured self-directed security selection, portfolio reallocation, buy/sell timing, and willingness to act on an investment judgment. Higher investment decision-making scores therefore indicate stronger decision engagement and action propensity; they do not represent objective investment quality or realized return performance.

Table 3. Construct operationalization

Construct	Code	Items	Operational meaning
Overconfidence	OC	4	Perceived superiority of personal knowledge, forecasting and investment judgment
Herding	HB	4	Reliance on market crowd, peers, popular investor behaviour and dominant market direction
Anchoring	AB	4	Dependence on purchase price, previous highs, target values or other salient numerical references
Loss aversion	LA	4	Disproportionate sensitivity to potential or realized losses relative to comparable gains
Disposition effect	DE	4	Preference to realize gains while postponing realization of losing positions
Representativeness	RB	4	Extrapolation from recent patterns, salient characteristics or perceived similarity
Financial risk propensity	FRP	5	Willingness to accept uncertain financial outcomes for higher expected return
Investment decision-making	IDM	5	Self-directed buy, sell, hold, timing and portfolio-allocation decisions

3.3 Data Quality, Common-Method Assessment and Analysis Strategy

Data screening included admissible-range checks, missing-value inspection, Mahalanobis-distance review, assessment of univariate skewness and kurtosis, and standardized residual diagnostics. No scale item had more than 1.6% missing values before case screening. Remaining isolated missing responses were replaced through respondent-level expectation-maximization estimation because the missingness pattern was nonsystematic.

Absolute skewness values ranged from 0.08 to 0.91 and absolute kurtosis values from 0.06 to 1.24, supporting maximum-likelihood estimation.

Procedural controls were used to reduce common-method bias: predictor and criterion blocks were separated, item wording avoided explicit causal cues, anonymity was emphasized, and the questionnaire mixed the order of bias dimensions. Statistically, Harman's unrotated single-factor solution accounted for 29.4% of total variance. A one-factor confirmatory model also fitted the data poorly (CFI = .612; RMSEA = .126), whereas the proposed eight-factor model demonstrated satisfactory fit. These results indicate that a single common factor did not dominate the covariance structure.

The analysis proceeded in four stages using IBM SPSS Statistics 29 and AMOS 29. First, descriptive statistics and a Friedman test identified the relative intensity of investor biases. Second, confirmatory factor analysis assessed factor loadings, Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity. Third, covariance-based structural equation modelling estimated the hypothesized paths and variance explained in financial risk propensity and investment decision-making. Fourth, indirect effects were evaluated with 5,000 bias-corrected bootstrap resamples. Robustness analysis re-estimated the decision model after controlling for age, gender, annual income, investment experience, and trading frequency. Statistical significance was evaluated at the .05 level, while effect sizes and confidence intervals were used to assess substantive importance.

4. Empirical Evidence

4.1 Investor Profile

Table 4. Profile of participating investors (N = 438)

Characteristic	Category	n	%
Region	Kerala	102	23.3
Region	Tamil Nadu	94	21.5
Region	Karnataka	88	20.1
Region	Telangana	82	18.7
Region	Andhra Pradesh	72	16.4
Gender	Male	286	65.3
Gender	Female	152	34.7
Age	18–30 years	159	36.3
Age	31–40 years	131	29.9
Age	41–50 years	88	20.1
Age	Above 50 years	60	13.7
Investment experience	Less than 2 years	95	21.7
Investment experience	2–5 years	139	31.7
Investment experience	6–10 years	112	25.6
Investment experience	More than 10 years	92	21.0
Trading frequency	Daily	71	16.2
Trading frequency	Weekly	148	33.8
Trading frequency	Monthly	139	31.7

Trading frequency	Occasional	80	18.3

The sample was geographically distributed across five southern states. Kerala accounted for 23.3% of respondents, followed by Tamil Nadu (21.5%), Karnataka (20.1%), Telangana (18.7%), and Andhra Pradesh (16.4%). Approximately 78.3% had at least two years of investment experience, and 50.0% traded at least weekly. The sample therefore represented a mixture of relatively new and experienced investors with meaningful exposure to ongoing market decisions.

4.2 Which Biases Were Most Pronounced?

Table 5. Relative intensity of investor biases

Bias	Mean	SD	Rank
Loss aversion	5.26	1.11	1
Overconfidence	4.96	1.02	2
Anchoring	4.73	1.08	3
Disposition effect	4.61	1.16	4
Representativeness	4.55	1.05	5
Herding	4.42	1.18	6

Note. All constructs were measured on a seven-point scale. Friedman test: $\chi^2(5) = 246.70$, $p < .001$; Kendall's W = .113.

Loss aversion recorded the highest mean score (M = 5.26), indicating that sensitivity to financial losses was the most pronounced behavioural tendency in the sample. Overconfidence ranked second, followed by anchoring. Herding produced the lowest mean, although its average remained above the neutral midpoint of the scale. The Friedman test confirmed that the six bias scores differed significantly, $\chi^2(5) = 246.70$, $p < .001$. Kendall's W of .113 indicated a modest but systematic ordering rather than a single dominant psychological profile shared uniformly by all investors. This pattern supports the first objective by showing that investor biases coexist but vary materially in relative strength.

4.3 Measurement Model: Reliability and Validity

Table 6. Measurement-model quality

Construct	Items	Loading range	α	CR	AVE	M	SD
Overconfidence (OC)	4	.79–.88	.864	.906	.707	4.96	1.02
Herding (HB)	4	.78–.86	.842	.894	.679	4.42	1.18
Anchoring (AB)	4	.77–.86	.836	.891	.672	4.73	1.08
Loss aversion (LA)	4	.82–.89	.887	.922	.747	5.26	1.11
Disposition effect (DE)	4	.79–.87	.853	.901	.695	4.61	1.16
Rep. bias (RB)	4	.75–.86	.821	.879	.646	4.55	1.05
Financial risk	5	.76–.85	.873	.910	.670	4.58	1.07

propensity (FRP)							
Investment decision-making (IDM)	5	.77–.87	.881	.915	.683	4.91	.96

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. All standardized loadings were significant at $p < .001$.

The eight-factor confirmatory model fitted the data satisfactorily: $\chi^2 = 752.84$, df = 398, $\chi^2/df = 1.89$, CFI = .954, TLI = .947, RMSEA = .045 (90% CI [.040, .050]), and SRMR = .041. All standardized factor loadings exceeded .75, Cronbach's alpha values ranged from .821 to .887, and composite reliability values ranged from .879 to .922. Average variance extracted exceeded .50 for every construct, establishing convergent validity. The highest heterotrait-monotrait ratio was .784, below the conservative .85 threshold, supporting discriminant validity. Variance inflation factors for the structural predictors ranged from 1.28 to 2.17, indicating that multicollinearity was not a material concern.

Table 7. Discriminant-validity diagnostic

Construct	Highest HTMT	Paired construct
OC	.742	HB
HB	.711	FRP
AB	.759	LA
LA	.784	DE
DE	.731	LA
RB	.702	OC
FRP	.746	IDM
IDM	.746	FRP

Note. All HTMT ratios were below .85.

4.4 Structural Relationships

Table 8. Structural-model estimates

Hyp.	Path	β	SE	z	p	95% CI	f²	Decision
H1a	OC → FRP	.273	.052	5.25	< .001	[.173, .373]	.083	Supported
H1b	HB → FRP	.186	.056	3.32	.001	[.077, .294]	.041	Supported
H1c	AB → FRP	.112	.050	2.25	.024	[.015, .211]	.016	Supported
H1d	LA → FRP	−.224	.048	−4.67	< .001	[−.318, −.131]	.061	Supported
H1e	DE → FRP	.091	.049	1.87	.061	[−.005, .187]	.010	Not supported
H1f	RB → FRP	.154	.052	2.98	.003	[.053, .256]	.027	Supported
H2a	OC →	.171	.054	3.17	.002	[.067,	.036	Supported

	IDM					.277]		
H2b	HB → IDM	.124	.052	2.39	.017	[.023, .226]	.020	Supported
H2c	AB → IDM	.097	.047	2.05	.041	[.005, .189]	.013	Supported
H2d	LA → IDM	−.138	.050	−2.75	.006	[−.237, −.040]	.024	Supported
H2e	DE → IDM	.116	.049	2.37	.018	[.020, .212]	.018	Supported
H2f	RB → IDM	.083	.047	1.76	.078	[−.009, .176]	.009	Not supported
H3	FRP → IDM	.364	.058	6.28	< .001	[.251, .478]	.147	Supported

Note. Standardized coefficients are reported. $R^2 = .421$ for financial risk propensity and $R^2 = .584$ for investment decision-making.

The structural model explained 42.1% of the variance in financial risk propensity and 58.4% of the variance in investment decision-making. Overconfidence had the largest positive effect on risk propensity (β = .273, p < .001), while loss aversion had the largest negative effect (β = −.224, p < .001). Herding and representativeness also produced meaningful positive effects. Anchoring reached statistical significance but had a comparatively small effect. The disposition effect did not independently predict generalized financial risk propensity (β = .091, p = .061), supporting the theoretical distinction between a gain-loss realization tendency and a broad willingness to accept financial uncertainty.

Financial risk propensity was the strongest direct predictor of investment decision-making (β = .364, p < .001). Overconfidence, herding, anchoring, the disposition effect, and loss aversion retained significant direct paths after risk propensity was included. Loss aversion reduced decision engagement, whereas the remaining significant biases increased it. Representativeness did not retain an independent direct effect (β = .083, p = .078), suggesting that its influence was more strongly channelled through the investor's risk orientation than through a separate transaction tendency.

4.5 Indirect Effects: Does Risk Propensity Transmit Bias?

Table 9. Bootstrapped mediation through financial risk propensity

Indirect path	Indirect β	Boot SE	95% bootstrap CI	Significant	Mediation pattern
OC → FRP → IDM	.099	.026	[.062, .144]	Yes	Partial
HB → FRP → IDM	.068	.019	[.033, .105]	Yes	Partial
AB → FRP → IDM	.041	.017	[.009, .078]	Yes	Partial
LA → FRP → IDM	−.082	.021	[−.126, −.044]	Yes	Partial
DE → FRP → IDM	.033	.019	[−.002, .071]	No	None through

					FRP
RB → FRP → IDM	.056	.018	[.021, .093]	Yes	Indirect-only

Note. 5,000 bias-corrected bootstrap resamples. An indirect effect is significant when the confidence interval excludes zero.

The mediation analysis clarified the mechanism connecting bias to investment behaviour. Financial risk propensity partially mediated the effects of overconfidence, herding, anchoring, and loss aversion because both their direct and indirect paths remained significant. Representativeness displayed indirect-only mediation: the bias increased risk propensity, and risk propensity increased investment decision-making, while the direct representativeness-to-decision path was nonsignificant. The disposition effect did not operate through risk propensity. This result is theoretically coherent because disposition behaviour concerns the realization of existing gains and losses rather than generalized willingness to assume uncertain financial exposure.

4.6 Robustness and Control Variables

Table 10. Robustness of investment-decision paths

Predictor	Main-model β	Controlled-model β	Controlled p	Assessment
Overconfidence	.171	.160	.004	Stable
Herding	.124	.116	.024	Stable
Anchoring	.097	.092	.047	Stable
Loss aversion	−.138	−.129	.009	Stable
Disposition effect	.116	.108	.025	Stable
Representativeness	.083	.076	.102	Nonsignificant in both
Risk propensity	.364	.347	< .001	Stable

Note. Controlled model included age, gender, annual income, investment experience, and trading frequency. R^2 for investment decision-making increased from .584 to .612.

The substantive findings remained stable after demographic and trading controls were added. The controlled model explained 61.2% of investment decision-making variance. Trading frequency had a positive independent effect ($\beta = .141$, $p = .003$), whereas age, gender, income, and experience produced comparatively small coefficients after the behavioural variables were entered. The structural conclusions concerning risk propensity and the principal biases were therefore not attributable to simple demographic composition.

5. Interpretation and Theoretical Contribution

5.1 Biases Are Unequal in Prevalence and Function

The first contribution is empirical differentiation. Loss aversion was the most pronounced bias, but overconfidence exerted the strongest positive effect on financial risk propensity. This distinction is important: prevalence and predictive influence are not interchangeable. A bias can be common without being the most powerful driver of risky action. The finding is consistent with prospect theory's emphasis on asymmetric responses to losses while also aligning with evidence that overconfidence alters perceived skill and reduces subjective uncertainty (Kahneman & Tversky, 1979; Bernile et al., 2025).

The relatively lower mean for herding should not be interpreted as insignificance. Herding remained a significant predictor of both risk propensity and investment decision-making. The result suggests that social information may become behaviourally consequential even when investors do not strongly self-identify as crowd followers. This interpretation is consistent with informational-cascade theory, in which individuals can rationalize imitation as information extraction rather than conformity (Bikhchandani et al., 1992).

5.2 Risk Propensity Explains How Bias Becomes Action

The strongest theoretical result is the mediating role of financial risk propensity. Behavioural biases did not influence investment decisions through a uniform pathway. Overconfidence, herding, anchoring, and representativeness increased risk propensity, while loss aversion reduced it. Risk propensity then exerted the largest direct effect on investment decision-making. This mechanism extends a simple bias-outcome interpretation by showing that investors first translate a cognitive or emotional tendency into a risk stance and then convert that stance into action. The result is consistent with recent evidence that behavioural dimensions influence financial risk propensity and that risk propensity materially shapes investment decisions (Islam et al., 2024).

The mediation structure is especially informative for representativeness. Its direct effect disappeared after risk propensity was introduced, but the indirect effect remained significant. This indicates that pattern-based judgment does not necessarily force a buy or sell decision by itself; instead, it can change the investor's willingness to accept uncertainty, which subsequently influences action. Such a result demonstrates why models that omit risk propensity can misclassify the role of specific biases.

5.3 Loss Aversion and Disposition Effect Are Related but Not Equivalent

Loss aversion and the disposition effect are often discussed together, but the present results support analytical separation. Loss aversion reduced both financial risk propensity and investment decision-making, whereas the disposition effect directly increased decision tendencies but did not significantly predict generalized risk propensity. This difference reflects the constructs' theoretical boundaries. Loss aversion concerns asymmetric valuation of gains and losses across risky choices; the disposition effect concerns the timing of realizing an existing gain or loss relative to a reference price. The result is consistent with recent behavioural risk-profiling evidence showing that loss aversion is not interchangeable with ordinary risk preference (van Dolder & Vandenbroucke, 2024).

5.4 Contribution to the South Indian Investor Literature

The study also extends region-specific behavioural-finance evidence. Earlier research in Delhi-NCR documented the prevalence of overconfidence, herding, optimism, and disposition tendencies and showed that biases vary with investor characteristics (Prosad et al., 2015). Punjab-based research likewise found strong roles for herding, loss aversion, and overconfidence (Jain et al., 2020). By extending the analysis to investors across Kerala, Tamil Nadu, Karnataka, Telangana, and Andhra Pradesh and modelling risk propensity as a behavioural mechanism, the present study broadens geographically fragmented Indian evidence toward an integrated explanatory model. The results are also consistent with recent Indian evidence that behavioural factors remain important despite greater market access, financial literacy initiatives, and digital investment infrastructure (Agarwal et al., 2025; Hans et al., 2026; Raj, 2026).

6. Practical and Regulatory Implications

6.1 Investor Education: Move from Knowledge to Behavioural Debiasing

Traditional investor education concentrates on products, diversification, return calculations, taxation, and fraud prevention. These components remain essential, but the results indicate that knowledge alone does not eliminate behavioural distortions. Education programmes can incorporate decision journals, pre-trade checklists, counterfactual analysis, reference-price resets, and explicit comparison between independent valuation and crowd signals. Overconfidence can be addressed by requiring investors to record confidence intervals around expected returns rather than point forecasts. Herding can be reduced by separating the reasons for a trade from the popularity of the trade. Anchoring can be addressed by asking investors to revalue a security without displaying the purchase price.

6.2 Advisory and Brokerage Risk Profiling

Risk profiling can be improved by separating willingness to bear risk from loss sensitivity and behavioural bias. A single conservative-to-aggressive score may conceal an investor who is highly loss averse but simultaneously overconfident, or an investor who is generally risk tolerant but displays a strong disposition effect after losses occur. Behavioural risk profiling can therefore complement conventional suitability assessment rather than replace it. The distinction is supported by evidence that loss aversion and standard risk-return preference capture different dimensions of investor intent (van Dolder & Vandenbroucke, 2024).

Brokerage interfaces can also incorporate behavioural safeguards without restricting investor autonomy. Examples include prompts that display portfolio concentration before a high-conviction trade, cooling-off reminders after rapid consecutive transactions, alerts when a sell decision is based solely on recent price movement, and performance dashboards that benchmark realized outcomes against passive alternatives. Such interventions are most useful when they increase reflection rather than merely add friction.

6.3 Regulatory Communication and Market Conduct

The findings have implications for securities-market communication. The SEBI Investor Survey 2025 emphasizes that investor confidence and risk perception are influenced by market infrastructure, disclosure quality, and regulatory reforms (SEBI, 2026). Behavioural insights can complement these institutional measures. Investor alerts concerning social-media tips, derivatives, concentrated trading, or rapidly rising securities can explicitly identify the psychological mechanisms that make such situations attractive. Behaviourally informed communication is likely to be more effective when it explains not only that an action is risky but also why investors may systematically underestimate that risk.

7. Conclusion, Limitations and Research Agenda

7.1 Conclusion

This study examined the role of six behavioural biases and financial risk propensity in the investment decision-making of 438 stock-market investors across South India. The evidence showed that investor biases were neither equally prevalent nor behaviourally equivalent. Loss aversion was the most pronounced tendency, whereas overconfidence was the strongest positive determinant of financial risk propensity. Financial risk propensity emerged as the central mechanism in the model and produced the largest direct effect on investment decision-making. It partially mediated the effects of overconfidence, herding, anchoring, and loss aversion and fully transmitted the effect of representativeness. The disposition effect influenced investment decisions directly but was not explained by generalized risk propensity.

The findings support a layered view of investor behaviour. Cognitive and emotional biases shape how information is interpreted; risk propensity determines how that interpretation is translated into tolerance for uncertain outcomes; and investment decisions reflect the final behavioural response. This framework provides a more precise explanation than models that either treat investors as fully rational or aggregate diverse biases into a single behavioural score.

7.2 Limitations

The cross-sectional design limits temporal interpretation and does not establish that the measured biases precede every subsequent market decision. Self-reported measures may differ from transaction-level behaviour, particularly for socially undesirable tendencies such as herding or excessive confidence. Although the sample covered five South Indian states, it was not drawn from a complete registry of all retail investors and therefore does not constitute a probability sample of the entire South Indian investor population. The investment decision-making construct measured behavioural engagement rather than portfolio performance; consequently, a higher score cannot be interpreted as superior investment quality. Market regime, asset class, leverage, and portfolio size were also outside the principal structural model.

7.3 Future Research Agenda

Future studies can link psychometric measures to anonymized transaction records to test whether reported bias predicts turnover, realized gains and losses, portfolio concentration, and drawdown behaviour. Longitudinal designs can examine whether investor biases change after bull and bear market episodes. Multi-group structural models can test whether the bias-risk-decision mechanism differs by age, gender, experience, financial literacy, and use of social-media information. Experimental work can further evaluate whether debiasing prompts, delayed order confirmation, reference-price masking, or portfolio feedback reduce specific behavioural distortions. A particularly important extension is to distinguish cash-equity investors from derivatives traders, because leverage and nonlinear payoff structures may amplify the relationship between behavioural bias and financial risk propensity.

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[23] **Appendix A. Measurement Items**

[24] **Overconfidence (OC)**

[25] OC1. I am confident that my ability to interpret market information is better than that of the average individual investor.

[26] OC2. My personal analysis usually enables me to identify attractive stocks before most investors recognize them.

[27] OC3. I rely strongly on my own judgment when my view differs from general market opinion.

[28] OC4. Successful past investment decisions increase my confidence in making subsequent market calls.

[29] **Herding (HB)**

[30] HB1. The buying or selling activity of other investors influences my own investment decisions.

[31] HB2. I pay attention to stocks that are receiving strong interest from a large number of investors.

[32] HB3. I feel more comfortable entering an investment when many other investors are taking a similar position.

[33] HB4. Market consensus affects the timing of my buy or sell decisions.

[34] **Anchoring (AB)**

[35] AB1. The price at which I originally purchased a stock remains important when I decide whether to sell it.

[36] AB2. Recent highs or lows influence my judgment of whether a stock is currently expensive or cheap.

[37] AB3. Analyst targets or widely discussed price levels remain in my mind when I value a stock.

[38] AB4. I revise an initial valuation only gradually even when new market information becomes available.

[39] **Loss Aversion (LA)**

[40] LA1. A financial loss affects me more strongly than an equivalent financial gain pleases me.

[41] LA2. I avoid investments when the possibility of loss appears substantial even if the expected return is attractive.

[42] LA3. I prefer protecting existing capital to pursuing a higher return when market uncertainty rises.

[43] LA4. The possibility of losing money can prevent me from acting on an otherwise attractive investment opportunity.

[44] **Disposition Effect (DE)**

[45] DE1. I tend to sell a stock after a satisfactory gain even when its longer-term prospects remain favourable.
[46] DE2. I am reluctant to sell a stock below my purchase price.
[47] DE3. I often continue holding a losing stock because I expect the price to return to my original purchase level.
[48] DE4. Realizing a gain feels easier than realizing a loss of similar size.
[49] **Representativeness (RB)**
[50] RB1. Recent strong performance makes me more likely to expect that a stock will continue to perform well.
[51] RB2. I use similarities with previously successful companies when evaluating a new investment opportunity.
[52] RB3. A short sequence of favourable market information can strongly influence my expectations about future performance.
[53] RB4. I sometimes treat a recent market pattern as evidence of a continuing trend.
[54] **Financial Risk Propensity (FRP)**
[55] FRP1. I am willing to accept substantial short-term price fluctuations for the possibility of higher long-term returns.
[56] FRP2. I can invest in an opportunity even when the outcome is uncertain if the expected return is sufficiently attractive.
[57] FRP3. I am comfortable allocating part of my portfolio to higher-risk equities.
[58] FRP4. Temporary losses do not automatically cause me to reduce exposure to a fundamentally attractive investment.
[59] FRP5. I am willing to accept a higher probability of loss when the potential return adequately compensates for that risk.
[60] **Investment Decision-Making (IDM)**
[61] IDM1. I make my own buy, hold, or sell decisions after evaluating available market information.
[62] IDM2. I actively adjust my portfolio when my assessment of market conditions changes.
[63] IDM3. I am prepared to act when I identify an investment opportunity that fits my analysis.
[64] IDM4. I make deliberate decisions about the timing and size of equity investments.
[65] IDM5. I regularly review whether current holdings remain consistent with my investment judgment.