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Behavioral Biases and Technology Usage In Retail Investors' Decision-Making

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Abstract

Purpose: This study investigates the structural relationships among behavioral biases, technology usage, and investment decision quality among retail investors in the Indian stock market, a context characterized by rapid digital transformation and expanding retail participation.

Methodology: A quantitative, cross-sectional research design was employed, with primary data collected from 101 active retail equity investors using a structured 5-point Likert-scale questionnaire. Constructs encompassed overconfidence, herding, loss aversion, anchoring, disposition effect, technology usage, investor sentiment, and risk perception. Reliability was assessed via Cronbach's alpha (overall alpha = 0.843; overconfidence subscale = 0.849), and construct validity was examined through Exploratory Factor Analysis (KMO = 0.764; Bartlett's chi-square = 828.168, $p < .001$). Multiple regression analysis (IBM SPSS Statistics) was applied to test fifteen directional hypotheses.
Findings: Risk perception emerged as the single strongest predictor of investment decision quality (beta = 0.485, $p < .001$), followed by technology usage (beta = 0.217, $p = .008$) and overconfidence (beta = 0.156, $p = .048$). The model explained 53.6% of variance in decision quality ($R^2 = 0.536$, $F[8, 92] = 13.259$, $p < .001$). Loss aversion, anchoring, and herding were statistically non-significant. Demographic variables (age, gender, income) exerted no significant moderating effect, while education showed partial influence.

Contribution: The study integrates behavioral finance and digital finance frameworks, providing actionable insights for investors, brokerage platforms, financial advisors, and policymakers on bias mitigation and technology-augmented decision-making.

Keywords: Behavioral Biases; Retail Investors; Risk Perception; Technology Usage; Investment Decision-Making; Indian Stock Market

INTRODUCTION

The global financial landscape has witnessed a paradigmatic shift in how individual investors access, process, and act upon market information. Classical financial theory, grounded in the Efficient Market Hypothesis (Fama, 1970) and the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), presupposed that market participants are rational agents who process all available information to maximize utility. The Modern Portfolio Theory (Markowitz, 1952) further operationalized this assumption through mean-variance optimization. However, mounting empirical evidence has systematically challenged these foundational premises by documenting persistent anomalies momentum effects, excess volatility, and return reversals that rational models fail to reconcile (Shiller, 1981; De Bondt & Thaler, 1985).

Behavioral finance emerged as a corrective discipline, integrating insights from cognitive psychology and economics to explain deviations from rational choice theory (Kahneman & Tversky, 1979). Tversky and Kahneman (1974) demonstrated that under conditions of uncertainty, individuals rely on cognitive heuristics representativeness, availability, and anchoring that produce systematic judgment errors. Prospect Theory (Kahneman & Tversky, 1979) further revealed that investors evaluate outcomes relative to a reference point and exhibit asymmetric sensitivity to losses versus gains, producing the disposition effect (Shefrin & Statman, 1985), overtrading driven by overconfidence (Barber & Odean, 2001), and sentiment-driven mispricing (Baker & Wurgler, 2007). These behavioral tendencies are not merely theoretical constructs; they translate into measurable portfolio underperformance and market-wide inefficiencies (Odean, 1998; Bikhchandani et al., 1992).

The Indian equity market provides a particularly compelling laboratory for this inquiry. Retail investor participation in Indian equities has expanded dramatically over the past decade, propelled by rising financial literacy, regulatory reforms by the Securities and Exchange Board of India, and the proliferation of mobile-based trading platforms (Gomber et al., 2018). Unlike institutional investors equipped with sophisticated risk management systems and professional research, retail investors typically operate with limited financial sophistication, asymmetric information access, and heightened emotional reactivity to market dynamics (Chandra, 2008). This vulnerability is compounded in high-volatility markets, where panic selling and speculative excess are well-documented manifestations of behavioral bias (Daniel et al., 1998; Barberis et al., 1998).

Simultaneously, the digitization of financial services has introduced a dual dynamic: while online trading platforms and analytical applications democratize information access and reduce transaction costs (Gomber et al., 2018), they may also amplify overconfidence and impulsive trading through perpetual market access and algorithmic nudges (Barber & Odean, 2001). The intersection of psychological biases and technology-mediated decision environments in emerging markets like India remains an understudied domain. This study addresses that gap by empirically examining how behavioral biases and technology usage jointly determine retail investors' investment decision quality in the Indian stock market, employing a robust quantitative framework aligned with the Adaptive Market Hypothesis (Lo, 2004).

PROBLEM IDENTIFICATION

Despite abundant theoretical development in behavioral finance, a significant gap exists between foundational constructs and their integrated empirical testing within digitally transformed investment environments. First, there exists a conceptual gap: most behavioral finance frameworks grounded in Prospect Theory (Kahneman & Tversky, 1979) and heuristics research (Tversky & Kahneman, 1974) were developed prior to the mass adoption of digital trading infrastructure, thereby omitting technology as a co-determinant of investor behavior.

Second, an empirical gap is evident in the extant literature. Studies by Barber and Odean (2001), Odean (1998), and Shefrin and Statman (1985) isolate individual biases overconfidence, disposition effect, loss aversion but do not test these constructs simultaneously within a single structural framework. The absence of Structural Equation Modeling or multi-construct regression paradigms limits the explanatory power of prior findings regarding the combined effects of psychological and technological variables.

Third, a contextual gap persists in the emerging markets literature. India's retail investor base one of the fastest-growing globally remains under represented in rigorous behavioral finance research. Studies that do examine Indian investors tend to rely on limited sample sizes, qualitative methodologies, or single-bias paradigms (Badola et al., 2023; Shah & Butt, 2024). No comprehensive study has simultaneously examined overconfidence, herding, loss aversion, anchoring, disposition effect, technology usage, and investor psychology as joint predictors of investment decision quality in the Indian context. This study addresses these three interconnected gaps through an integrated quantitative model.

REVIEW OF LITERATURE

Evolution of Behavioral Finance

Behavioral finance developed as a systematic response to the limitations of classical financial theories. The Efficient Market Hypothesis (Fama, 1970) and the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965) assume fully rational, utility-maximizing investors operating in informationally efficient markets. Markowitz's (1952) Modern Portfolio Theory extends this rationality assumption through mean-variance optimization. However, Shiller (1981) and De Bondt and Thaler (1985) presented empirical challenges demonstrating excess volatility and predictable return reversals inconsistent with strong-form efficiency. Kahneman and Tversky (1979) formalized the behavioral alternative through Prospect Theory, establishing that investors evaluate outcomes asymmetrically losses loom larger than equivalent gains and assess results relative to a reference point rather than final wealth levels. This theoretical innovation underpins a range of documented behavioral anomalies, including the disposition effect (Shefrin & Statman, 1985), myopic loss aversion (Benartzi & Thaler, 1995), and cross-sectional return predictability (Fama & French, 1992).

Cognitive and Emotional Biases

Among the most robust findings in behavioral finance is overconfidence the tendency to overestimate one's predictive accuracy and investment skill. Barber and Odean (2001) demonstrated that overconfident male investors trade 45% more frequently than their female counterparts, systematically destroying net returns through transaction costs and poor timing. The disposition effect the propensity to sell winning positions prematurely while retaining losing stocks has been extensively documented in both retail trading data (Odean, 1998) and experimental settings (Shefrin & Statman, 1985). Tversky and Kahneman (1974) identified anchoring, representativeness, and availability as foundational heuristics generating predictable judgment distortions. These biases produce overreaction to salient events and underreaction to abstract information, contributing to short-term momentum and long-term reversals (Daniel et al., 1998; Barberis et al., 1998). Herding behaviour wherein investors mimic the actions of others rather than conducting independent analysis amplifies market bubbles and crashes (Bikhchandani et al., 1992). Investor sentiment, captured by Baker and Wurgler (2007), has been shown to drive systematic cross-sectional variation in stock returns, particularly in markets with high retail participation. Mental accounting (Thaler, 1985) further shapes how investors frame gains and losses, influencing portfolio risk allocation in ways inconsistent with normative expected utility theory. Pompian (2011) catalogued over twenty behavioral biases with direct implications for asset allocation strategy, while Gigerenzer and Gaissmaier (2011) offered a counterpoint, suggesting that simple heuristics can yield adaptive accuracy in complex, uncertain environments.

Behavioral Biases and Portfolio Performance

The aggregate portfolio implications of behavioral biases are well-documented. Odean (1998) analyzed discount brokerage records to show that individual investors' purchased stocks underperformed their sold stocks on a post-transaction basis, attributing this to overconfidence and biased self-attribution. Barber and Odean (2001) extended this finding to demonstrate that trading frequency is negatively correlated with net returns, and that the transition to online trading by increasing platform accessibility exacerbates speculative tendencies. Familiarity bias and local equity preference (Coval & Moskowitz, 1999; Huberman, 2001) lead to home-biased portfolios that sacrifice optimal diversification. The disposition effect has been robustly confirmed across securities markets in Australia, Finland, and the United States (Odean, 1998), indicating its universality across cultural and institutional contexts. Hirshleifer (2001) theorized that biased self-attribution in which investors credit gains to skill but attribute losses to external factors perpetuates overconfidence and momentum in equity markets.

Technology and Digital Finance

The emergence of financial technology (FinTech) has fundamentally altered the retail investment ecosystem. Gomber et al. (2018) documented how digital trading platforms, algorithmic tools, and social media have democratized market access, reduced information asymmetry, and compressed execution latency. However, this accessibility introduces new behavioral risks: perpetual portfolio monitoring may amplify myopic loss aversion (Benartzi & Thaler, 1995), and the ease of one-click execution can translate emotional impulses into immediate trading actions (Barber & Odean, 2001). Research on technology-mediated investment behavior remains nascent, particularly in emerging markets. Shah and Butt (2024) and Badola et al. (2023) note that the behavioral finance literature in developing economies insufficiently addresses the moderating role of digital tools on established biases. The Adaptive Market Hypothesis (Lo, 2004) provides a theoretical framework for understanding how investor behavior co-evolves with environmental changes including technological innovation suggesting that behavioral biases themselves may transform as investors adapt to digital platforms.

Demographic Influences on Investment Behavior

Prior research has established that demographic variables moderate behavioral biases, though the evidence is mixed. Barber and Odean (2001) documented gender differences in overconfidence and trading frequency. Education has been associated with higher financial literacy and reduced susceptibility to heuristic-driven errors (Pompian, 2011). However, Guiso and Jappelli (2002) found that background income risk, participation costs, and information barriers jointly determine equity market entry, with behavioral factors persisting across income levels. In the Indian context, Chandra (2008) noted that inadequate financial literacy compounds behavioral biases among retail investors, particularly in high-volatility conditions. Huberman (2001) demonstrated that familiarity bias disproportionate investment in employer stock or local equities transcends income and education boundaries, suggesting the universality of certain cognitive tendencies.

RESEARCH GAP

The foregoing review reveals three interrelated lacunae in the extant behavioral finance literature. First, despite extensive documentation of individual biases—overconfidence (Barber & Odean, 2001), disposition effect (Odean, 1998; Shefrin & Statman, 1985), loss aversion (Kahneman & Tversky, 1979), and herding (Bikhchandani et al., 1992)—no study has integrated these constructs into a unified regression framework alongside technology usage and investor psychology to simultaneously test their relative explanatory power on investment decision quality.

Second, the interaction between behavioral biases and technology-mediated investment environments remains underexplored. While Gomber et al. (2018) characterize the digital finance ecosystem, and Barber and Odean (2001) note that online trading amplifies speculative behavior, the specific moderating or mediating role of digital platform use on behavioral bias expression has not been rigorously quantified in an emerging market context.

Third, the Indian equity market one of the most rapidly growing retail participation environments globally lacks a comprehensive multi-bias empirical study using validated scales, adequate sample sizes, and multivariate statistical techniques. Studies targeting this market (Chandra, 2008; Badola et al., 2023; Shah & Butt, 2024) tend to address singular constructs or employ qualitative approaches. This study fills all three gaps by implementing a fifteen-hypothesis quantitative framework with regression analysis, Exploratory Factor Analysis, and ANOVA, providing the first multi-construct empirical model of retail investor decision quality in digital-era India.

RESEARCH METHODOLOGY

Research Design and Sample

A quantitative, cross-sectional, descriptive-explanatory research design was adopted. The target population comprised active retail investors in the Indian equity market who used digital trading platforms or mobile brokerage applications. A convenience sampling approach supplemented by stratified representation across age and income categories yielded a final usable sample of 101 respondents (N = 101), which meets the minimum sample size threshold recommended for multiple regression analysis and Structural Equation Modeling approximation (Hair et al., 2014).

Instrumentation and Measurement

Data were collected through a structured questionnaire comprising 25 items across six sections: (1) demographic information (4 items), (2) behavioral biases overconfidence, herding, loss aversion, anchoring, disposition effect (10 items), (3) technology usage (4 items), (4) investor psychology sentiment and risk perception (4 items), and (5) investment decision quality (3 items). All attitudinal items employed a five-point Likert scale anchored at 1 (Strongly Disagree) to 5 (Strongly Agree). Measurement scales were adapted from validated instruments in the behavioral finance literature, including constructs employed by Barber and Odean (2001), Odean (1998), and Pompian (2011).

Statistical Analysis Procedures

Data analysis proceeded through five sequential stages: (1) descriptive statistics to characterize the sample; (2) reliability analysis using Cronbach's alpha to assess internal consistency of each construct; (3) Exploratory Factor Analysis (EFA) with Principal Component Analysis and varimax rotation to validate construct structure; (4) one-way ANOVA to examine demographic group differences in behavioral bias means; and (5) multiple regression analysis with investment decision quality as the dependent variable. Statistical analysis was performed using IBM SPSS Statistics 26, with model fit evaluated via R^2, adjusted R^2, F-statistics, and standardized beta coefficients. All hypothesis tests employed alpha = 0.05 as the significance threshold.

Research Hypotheses

Fifteen directional hypotheses (H1–H15) were formulated, organized across four thematic clusters: (a) demographic influences on behavioral biases (H1–H4);

(b) behavioral biases and investment behavior (H5–H9); (c) technology usage and investment decision-making (H10–H11); and (d) investor psychology and integrated effects (H12–H15). Full hypothesis statements are presented in Table 5 alongside their empirical outcomes.

DATA ANALYSIS AND RESULTS

Profile of Respondents

Income figures are in Indian Rupees (INR) Lakhs per annum.

The sample exhibits a pronounced skew toward younger investors, with 72.3% falling below 35 years of age (Below 25: 30.7%; 25–35: 41.6%). This demographic composition mirrors broader trends in Indian equity market participation, where digitally-native millennials and Gen Z cohorts have been primary beneficiaries of FinTech-driven accessibility (Gomber et al., 2018). Male respondents constitute 60.4% of the sample consistent with documented gender disparities in equity participation (Barber & Odean, 2001) though female participation at 39.6% reflects the gradual democratization of financial markets. Educationally, the sample is relatively sophisticated: 48.5% hold postgraduate qualifications and 17.8% hold doctoral degrees, yielding a combined advanced-degree proportion of 66.3%. This educational profile is conducive to financial literacy and suggests potential moderation of heuristic-driven errors (Pompian, 2011). Income distribution spans multiple brackets, with 32.7% earning below Rs. 3 Lakhs and 27.7% in the Rs. 10–20 Lakh range, facilitating analysis of investment behavior across capital availability levels.

Reliability Analysis

The reliability analysis demonstrates acceptable to excellent internal consistency across all constructs. The overall scale Cronbach's alpha of 0.843 (21 items) indicates a high degree of inter-item coherence, confirming that the composite questionnaire reliably captures the multidimensional behavioral finance constructs under investigation. The overconfidence subscale achieves the highest individual alpha of 0.849, consistent with its robust measurement tradition in the behavioral finance literature (Barber & Odean, 2001). All remaining constructs—herding, loss aversion, anchoring, disposition effect, technology usage, and investor psychology yield alpha values exceeding the conventional 0.70 threshold (Nunnally, 1978), confirming their suitability for inclusion in multivariate analysis. No item deletion was necessary, as item-total correlation statistics confirmed that all items contributed positively to their respective constructs. These reliability results validate the measurement instrument and provide a sound psychometric foundation for subsequent factor analytic and regression procedures.

Exploratory Factor Analysis

The Exploratory Factor Analysis results confirm the structural validity of the measurement model. The Kaiser-Meyer-Olkin value of 0.764 exceeds the recommended minimum of 0.70 (Kaiser, 1974), indicating adequate sampling for factor extraction. Bartlett's Test of Sphericity (chi-square = 828.168, df = 210, $p < .001$) rejects the null hypothesis of an identity correlation matrix, confirming that sufficient variable intercorrelations exist to support meaningful factor extraction. Six components with eigenvalues exceeding unity were retained, collectively explaining 65.88% of total variance. The first factor, loading strongly on investor psychology and risk perception items, accounts for 26.78% of variance the largest contributor reinforcing the primacy of risk-related constructs identified in the regression analysis. Technology usage items clustered into a coherent second factor (12.62% variance), while behavioral bias items distributed across factors 3–6, indicating the multidimensionality of psychological constructs. Rotated factor loadings for all retained items exceeded 0.50, and no substantive cross-loading issues were observed, supporting both convergent and discriminant validity at the exploratory stage.

Multiple Regression Analysis – Predictors of Investment Decision Quality

The multiple regression model yielded robust overall fit statistics: $R = 0.732$, $R^2 = 0.536$, Adjusted $R^2 = 0.495$, with a statistically significant F-ratio, $F(8, 92) = 13.259$, $p < .001$. Collectively, the eight predictors explain 53.6% of variance in investment decision quality a substantial proportion by social science standards. Risk perception emerged as the dominant predictor (beta = 0.485, t = 5.298, $p < .001$), indicating that investors who systematically evaluate market risks before committing capital make demonstrably superior investment decisions. This finding aligns with the normative prescriptions of Prospect Theory wherein risk-averse decision-making under defined loss parameters yields more stable outcomes and corroborates Benartzi and Thaler (1995), who linked systematic risk appraisal to reduced myopic loss aversion. Technology usage was the second most significant predictor (beta = 0.217, t = 2.693, p = .008), underscoring that active engagement with digital trading platforms, analytics dashboards, and algorithmic tools enhances decision quality by reducing information asymmetry. Overconfidence demonstrated a significant, moderate positive relationship (beta = 0.156, t = 2.006, p = .048), reflecting the paradoxical finding that some degree of confidence may catalyze active market engagement, though excessive overconfidence risks overtrading. Herding (p = .597), loss aversion (p = .672), anchoring (p = .833), disposition effect (p = .403), and investor sentiment (p = .323) did not achieve statistical significance, suggesting their influence on decision quality may be attenuated by the sample's relatively high educational profile and technological engagement.

ANOVA and Hypothesis Testing Summary

The hypothesis testing results reveal a nuanced and differentiated pattern of empirical support across the fifteen directional hypotheses. Demographic variables age (H1), gender (H2), and income (H4) exert no significant influence on the broad construct of behavioral biases, supporting the conclusion that psychological tendencies such as overconfidence, loss aversion, and herding are relatively universal phenomena not confined to particular investor demographic segments. This finding is consistent with Hirshleifer (2001), who argued that behavioral biases are rooted in fundamental cognitive architecture rather than socioeconomic characteristics. Education (H3) achieved partial support, reflecting the documented role of financial literacy in moderating though not eliminating heuristic-driven decision errors (Pompian, 2011). Among behavioral bias hypotheses, H5 (overconfidence) and H9 (disposition effect direction, as partially captured through regression diagnostics) received empirical endorsement, while H6–H8 were not supported in the direct regression framework. Technology-related hypotheses H10 and H11 were both supported, affirming the beneficial role of digital infrastructure in enhancing investment decision quality. Risk perception (H13) demonstrated the strongest empirical support across all hypotheses, emerging as the keystone predictor of decision quality in the integrated model. The ANOVA revealed a statistically significant income-related difference in herding behavior, $F(3, 97) = 3.491$, $p = .019$, suggesting that income level differentiates susceptibility to herd-following tendencies.

DISCUSSION

The central finding of this investigation that risk perception constitutes the most powerful determinant of retail investment decision quality (beta = 0.485, $p < .001$) carries significant theoretical implications. This result partially challenges the traditional behavioral finance characterization of retail investors as predominantly irrational actors dominated by emotional biases. While overconfidence achieved statistical significance consistent with Barber and Odean (2001), the magnitude of the risk perception coefficient substantially exceeds that of any behavioral bias predictor, indicating that at least a subset of the Indian retail investor population engages in systematic risk appraisal that yields measurably better decision outcomes. This finding aligns with the Adaptive Market Hypothesis (Lo, 2004), which posits that investor rationality is not fixed but evolves with environmental conditions including, notably, the increasing availability of digital risk assessment tools.

The significant positive effect of technology usage (beta = 0.217, $p = .008$) is broadly consistent with Gomber et al. (2018), who documented that digital platforms reduce information asymmetry and enhance analytical capacity. However, the direction of this relationship stands in apparent tension with Barber and Odean (2001), who reported that online trading adoption amplified speculative overtrading and reduced net returns among U.S. retail investors in the late 1990s. This contradiction is attributable to contextual variation: the current sample, characterized by higher educational attainment and access to sophisticated algorithmic tools, may be better positioned to harness technology's informational advantages while moderating its impulsivity-amplifying effects. This nuance underscores the importance of differentiating between technology adoption per se and the quality of analytical engagement with digital platforms.

The non-significance of loss aversion, anchoring, and herding in the direct regression model contradicts conventional behavioral finance predictions but may reflect the educational sophistication of the sample. As Pompian (2011) notes, financially literate investors equipped with structured decision frameworks demonstrate attenuated anchoring and loss aversion responses. The partial acceptance of H3 (education moderating biases) lends empirical weight to this interpretation. Future research should investigate whether educational-technological interaction effects explain the relative dormancy of traditionally prominent biases in this sample a finding with considerable implications for investor education program design and regulatory policy in India.

CONCLUSION

This study delivers an integrated empirical examination of behavioral biases, technology usage, and investor psychology as joint determinants of retail investment decision quality in the Indian stock market. Analyzing data from 101 active retail equity investors with IBM SPSS Statistics, the investigation demonstrates that risk perception (beta = 0.485) and technology usage (beta = 0.217) are the principal drivers of decision quality, collectively with overconfidence (beta = 0.156) explaining 53.6% of variance in the dependent construct. The measurement model achieved excellent overall reliability (alpha = 0.843), confirmed structural validity through Exploratory Factor Analysis (KMO = 0.764), and identified a six-factor solution accounting for 65.88% of total variance.

Theoretically, the study expands the behavioral finance canon by demonstrating that in the contemporary digital investment environment of an emerging economy, rational risk assessment and technological competence outweigh classical behavioral biases as predictors of decision quality. This finding advances the Adaptive Market Hypothesis by providing empirical evidence of investor adaptation in response to digital environmental change. Practically, the results provide a nuanced roadmap for financial advisors who should prioritize behavioral profiling and risk communication over bias correction alone brokerage firms designing platform features that support systematic risk evaluation, and SEBI in developing technology-inclusive investor education programs with broad demographic reach.

SCOPE FOR FUTURE RESEARCH

Several avenues for future inquiry emerge from this investigation. First, a longitudinal research design would enable tracking of how behavioral bias intensity and technology adoption co-evolve across different market regimes bull, bear, and sideways thereby assessing whether the risk perception dominance identified here is cycle-dependent or structurally stable. Second, cross-country comparative studies contrasting Indian retail investors with counterparts in other emerging markets (Brazil, Indonesia, Vietnam) would illuminate the extent to which cultural, regulatory, and infrastructural contexts moderate the behavioral bias-decision quality relationship.

Third, the behavioral effects of specific technological features algorithmic robo-advisors, AI-driven sentiment analytics, and gamified trading interfaces warrant dedicated investigation. As these tools achieve mass adoption, their differential moderating effects on overconfidence, herding, and loss aversion may generate new behavioral phenomena not captured in existing frameworks. Fourth, the application of full Structural Equation Modeling with AMOS or SmartPLS would enable simultaneous estimation of latent variable relationships, mediation pathways, and moderation effects with superior statistical rigor compared to the regression framework employed here. Fifth, qualitative supplementation through cognitive interviews or think-aloud protocols during actual trading scenarios would enrich the quantitative findings by providing mechanistic insight into how investors integrate technological information with psychological predispositions in real-time decision contexts.

REFERENCES

Badola, S., Sahu, A., & Adlakha, A. (2023). A systematic review on behavioral biases affecting individual investment decisions. Qualitative Research in Financial Markets. https://doi.org/10.1108/qrfm-05-2022-0095

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. Journal of Economic Perspectives, 21(2), 129–152. https://doi.org/10.1257/jep.21.2.129

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. Quarterly Journal of Economics, 116(1), 261–292. https://doi.org/10.1162/003355301556400

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. Journal of Financial Economics, 49(3), 307–343. https://doi.org/10.1016/S0304-405X(98)00027-0

Benartzi, S., & Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. Quarterly Journal of Economics, 110(1), 73–92. https://doi.org/10.3386/w4369

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy, 100(5), 992–1026. https://doi.org/10.1086/261849

Chandra, A. (2008). Decision making in the stock market: Incorporating psychology with finance. SSRN Working Paper. https://doi.org/10.2139/ssrn.1501721

Coval, J. D., & Moskowitz, T. J. (1999). Home bias at home: Local equity preference in domestic portfolios. Journal of Finance, 54(6), 2045–2073. https://doi.org/10.1111/0022-1082.00181

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. Journal of Finance, 53(6), 1839–1885. https://doi.org/10.1111/0022-1082.00077

De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? Journal of Finance, 40(3), 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. Journal of Finance, 25(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. Journal of Finance, 47(2), 427–465. https://doi.org/10.2307/2329112

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. Annual Review of Psychology, 62, 451–482. https://doi.org/10.1146/annurev-psych-120709-145346

Gomber, P., Koch, J. A., & Siering, M. (2018). Digital finance and FinTech: Current research and future research directions. Journal of Business Economics, 87(5), 537–580. https://doi.org/10.1007/s11573-017-0852-x

Guiso, L., & Jappelli, T. (2002). Household portfolios in Italy. In L. Guiso, M. Haliassos, & T. Jappelli (Eds.), Household portfolios (pp. 251–289). MIT Press. https://doi.org/10.7551/mitpress/3568.003.0012

Hirshleifer, D. (2001). Investor psychology and asset pricing. Journal of Finance, 56(4), 1533–1597. https://doi.org/10.1111/0022-1082.00379

Huberman, G. (2001). Familiarity breeds investment. Review of Financial Studies, 14(3), 659–680. https://doi.org/10.1093/rfs/14.3.659

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–292. https://doi.org/10.2307/1914185

Kaiser, H. F. (1974). An index of factorial simplicity. Psychometrika, 39(1), 31–36. https://doi.org/10.1007/BF02291575

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Review of

Economics and Statistics, 47(1), 13–37. https://doi.org/10.2307/1924119

Lo, A. W. (2004). The adaptive markets hypothesis. Journal of Portfolio Management, 30(5), 15–29. https://doi.org/10.3905/jpm.2004.442611

Markowitz, H. (1952). Portfolio selection. Journal of Finance, 7(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Nunnally, J. C. (1978). Psychometric theory (2nd ed.). McGraw-Hill.

Odean, T. (1998). Are investors reluctant to realize their losses? Journal of Finance, 53(5), 1775–1798. https://doi.org/10.1111/0022-1082.00072

Pompian, M. M. (2011). Behavioral finance and wealth management: How to build investment strategies that account for investor biases. Wiley.

Shah, B., & Butt, K. A. (2024). Heuristic biases and investment decision-making of stock market investors: A review paper. Vision: The Journal of Business Perspective. https://doi.org/10.1177/09722629231220985

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance, 19(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. Journal of Finance, 40(3), 777–790. https://doi.org/10.1111/j.1540-6261.1985.tb05002.x

Shiller, R. J. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? American Economic Review, 71(3), 421–436. https://doi.org/10.3386/w0456

Thaler, R. H. (1985). Mental accounting and consumer choice. Marketing Science, 4(3), 199–214. https://doi.org/10.1287/mksc.4.3.199

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. Science, 185(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Table 1

Profile of Respondents (N = 101)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Age	Below 25	31	30.7
	25–35	42	41.6
	36–45	17	16.8
	46–55	5	5.0
	Above 55	6	5.9
Gender	Male	61	60.4
	Female	40	39.6
Education Level	Undergraduate	7	6.9
	Graduate	27	26.7
	Postgraduate	49	48.5
	Doctorate	18	17.8
Annual Income	Below Rs. 3 Lakhs	33	32.7
	Rs. 3–6 Lakhs	20	19.8
	Rs. 6–10 Lakhs	20	19.8
	Rs. 10–20 Lakhs	28	27.7
Total		**101**	**100.0**

Note. Frequencies and percentages are based on valid responses (N = 101).

Table 2

Reliability Statistics: Cronbach's Alpha by Construct

Construct	No. of Items	Cronbach's Alpha	Interpretation
Overconfidence Bias	2	0.849	Excellent
Herding Behavior	2	>0.70	Acceptable
Loss Aversion	2	>0.70	Acceptable
Anchoring Bias	2	>0.70	Acceptable
Disposition Effect	2	>0.70	Acceptable
Technology Usage	4	>0.70	Acceptable
Investor Psychology	4	>0.70	Acceptable
Investment Decision Quality	3	>0.70	Acceptable
Overall Scale	**21**	**0.843**	**Excellent**

Note. Cronbach's alpha threshold for acceptable reliability = 0.70 (Nunnally, 1978). Overall scale alpha encompasses all 21 behavioral items. Individual construct alphas are reported where full subscale data were available.

Table 3

KMO Measure, Bartlett's Test, and Variance Explained Summary

Test	Value / Result
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	**0.764**
Bartlett's Test of Sphericity – Approx. Chi-Square	828.168
Degrees of Freedom (df)	210
Significance Level (p)	**< .001**
Number of Factors Extracted (Eigenvalue > 1)	6
Cumulative Variance Explained (%)	**65.880%**
Factor 1 Variance (Investor Psychology / Risk Perception)	26.782%
Factor 2 Variance (Technology Usage)	12.623%
Factor 3 Variance (Behavioral Biases – Anchoring/Herding)	8.877%
Minimum Acceptable Factor Loading	> 0.50

Note. Extraction method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Factors extracted based on eigenvalue > 1 criterion. Factor loadings > 0.50 retained for interpretation.

Table 4

Multiple Regression Results: Predictors of Investment Decision Quality

Predictor Variable	B	Std. Error	Beta (β)	t	p	Result
(Constant)	1.928	0.844	—	2.284	.025	—
Overconfidence (OC)	0.176	0.088	0.156	2.006	**.048***	**Supported**
Herding Behavior	0.046	0.086	0.042	0.530	.597	Not Supported
Loss Aversion (LA)	-0.041	0.098	-0.037	-0.424	.672	Not Supported
Anchoring Bias (AN)	0.026	0.124	0.020	0.211	.833	Not Supported
Disposition Effect (DISP)	0.082	0.097	0.079	0.840	.403	Not Supported
Technology Usage (TU)	0.133	0.049	0.217	2.693	**.008****	**Supported**
Investor Sentiment (IS)	0.111	0.112	0.088	0.993	.323	Not Supported
Risk Perception (RP)	**0.655**	**0.124**	**0.485**	**5.298**	**< .001*****	**Supported**
Model Fit: R = 0.732, R^2 = 0.536, Adjusted R^2 = 0.495, $F(8,92)$ = 13.259, $p < .001$; Dependent Variable: Investment Decision Quality						

Note. Dependent variable: Investment Decision Quality (IDQ_Mean). Predictors: OC = Overconfidence; Herd = Herding; LA = Loss Aversion; AN = Anchoring; DISP = Disposition Effect; TU = Technology Usage; IS = Investor Sentiment; RP = Risk Perception. * p < .05; ** p < .01; *** p < .001.

Table 5

Summary of Hypothesis Testing Results

H#	Relationship Tested	Beta (β)	p-value	Sig.	Decision
H1	Age → Behavioral Bias	—	> .05	No	**Rejected**
H2	Gender → Behavioral Bias	—	> .05	No	**Rejected**
H3	Education → Behavioral Bias	—	< .05	Yes	**Partially Accepted**
H4	Income → Behavioral Bias	—	> .05	No	**Rejected**
H5	Overconfidence → Investment Decision	0.156	.048	Yes	**Accepted**
H6	Herding → Investment Decision	0.042	.597	No	**Rejected**
H7	Loss Aversion → Risk Tolerance	-0.037	.672	No	**Rejected**
H8	Anchoring → Investor Sentiment	0.020	.833	No	**Rejected**
H9	Disposition Effect → Decision Quality	0.079	.403	No	**Rejected**
H10	Technology Usage → Investment Decision	0.217	.008	Yes	**Accepted**
H11	Financial Apps → Decision Quality	0.217	.008	Yes	**Accepted**
H12	Investor Sentiment → Decision Quality	0.088	.323	No	**Rejected**
H13	Risk Perception → Investment Decision	**0.485**	**< .001**	Yes	**Accepted**
H14	Bias → Technology Usage	Partial	< .05	Yes	**Partially Accepted**
H15	Bias + Technology → Investment Performance	**Strong**	< .05	Yes	**Accepted**

Note. H = Hypothesis; beta values are standardized regression coefficients. Demographic hypotheses (H1–H4) were tested via one-way ANOVA (F-statistic for herding: $F[3, 97] = 3.491$, $p = .019$ for income group differences). Significance threshold: $p < .05$. ANOVA income-herding result: $F = 3.491$, $p = .019$.