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**Research Article**

# Behavioral Determinants of Investment Decision-Making in the Indian Equity Market: An Integrative Review and Conceptual Framework for BSE and NSE Investors

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**Abstract**
This article addresses the objective of identifying and evaluating the principal behavioral factors that shape investment decisions in the Indian equity market. It develops an integrative framework for retail investors who participate through the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). Standard finance assumes that investors process information consistently and select portfolios by balancing expected return and risk. In practice, bounded attention, reference dependence, social influence, emotional responses, and limited financial capability cause systematic departures from that benchmark. Drawing on foundational behavioral-finance theory, international evidence, Indian investor studies, and the Securities and Exchange Board of India's Investor Survey 2025, the article synthesizes ten recurring influences: overconfidence, loss aversion, the disposition effect, herding, anchoring, representativeness, availability and recency, mental accounting, familiarity, and regret aversion. The synthesis indicates that these factors do not operate independently. Digital trading access, social media, market volatility, financial literacy, investment experience, and demographic conditions can strengthen, weaken, or redirect their effect on participation, security selection, trading frequency, diversification, and exit decisions. The article contributes a context-sensitive conceptual model and eight propositions suitable for testing with BSE- and NSE-linked investor samples, transaction records, experiments, or mixed methods. It also recommends bias-aware suitability assessment, decision checklists, cooling-off mechanisms, portfolio-level reporting, and targeted investor education. The central argument is that investor protection and decision quality in India require an approach that combines market information, financial capability, platform design, and behavioral diagnostics rather than relying on information disclosure alone.
**Keywords:** behavioral finance, investment decision-making, Indian stock market, BSE, NSE, investor bias, financial literacy, retail investors.

## 1. Introduction

The rapid expansion of electronic brokerage, app-based investing, low-cost execution, and digital financial information has widened access to Indian equities. Yet access does not automatically produce well-calibrated decisions. A securities market can disseminate prices quickly while individual investors still interpret the same price, disclosure, or news event through different psychological frames. Investment decision-making therefore includes more than the decision to buy a share. It encompasses whether to participate, which security to select, how much capital to allocate, when to enter, how long to hold, whether to diversify, and when to sell. Each stage can be affected by cognition, emotion, social interaction, and the design of the trading environment.

Traditional finance provides the essential normative benchmark for these choices. Under expected-utility reasoning and the efficient market perspective, investors compare risk-adjusted expected returns, use available information without systematic error, and avoid trading when the expected benefit does not exceed cost. Fama (1970) formalized market efficiency as the extent to which prices reflect available information. The framework is indispensable for evaluating price formation, but it does not imply that every investor is fully rational or that every decision is optimal. Behavioral finance complements rather than simply rejects the standard model by explaining why actual choices can diverge predictably from the normative benchmark (Barberis & Thaler, 2003; Hirshleifer, 2001).

The Indian context makes this inquiry particularly important. The Securities and Exchange Board of India’s nationwide Investor Survey 2025 reports high awareness of at least one securities product but much lower household participation. It also identifies substantial dormancy among existing investors, widespread preference for capital preservation, knowledge gaps, complexity concerns, and heavy reliance on digital information channels and financial influencers (Securities and Exchange Board of India [SEBI], 2026). These patterns indicate that the distance between awareness, participation, and sustained investing cannot be explained by information availability alone. Perceived risk, trust, confidence, salience, social proof, and prior experience are likely to shape whether information is acted upon and how it is translated into a trade.

Indian empirical studies already document the relevance of behavioral influences, but their findings are fragmented across regions, investor categories, measures, and market conditions. Prosad et al. (2015) found overconfidence, optimism, herding, and the disposition effect among investors in the Delhi-NCR region, with behavioral variation across age, profession, and trading frequency. Mishra and Metilda (2015) showed that experience, education, and gender are related to overconfidence and self-attribution. Raut et al. (2020), Haritha and Uchil (2020), Das and Panja (2022), and Shukla et al. (2024) similarly demonstrate that investor decisions are influenced by psychological, social, market, and informational variables. At the market level, evidence on herding is conditional rather than uniform: it varies across market direction, liquidity, volatility, and crisis periods (Ansari & Ansari, 2021; Lao & Singh, 2011).

Three gaps follow from this literature. First, many studies examine one or two biases in isolation even though actual decisions often arise from interacting biases. For example, attention to a rising stock may activate representativeness, social proof, overconfidence, and fear of missing out at the same time. Second, behavioral variables are sometimes treated as direct causes of a broad “investment decision” construct without distinguishing participation, stock selection, trade intensity, portfolio concentration, and realization behavior. Third, Indian research remains geographically concentrated and frequently relies on cross-sectional self-reports. There is a need for a framework that connects specific behavioral mechanisms to specific decision outcomes and identifies the conditions under which those relationships should become stronger or weaker.

Accordingly, this article selects the study objective “to identify and evaluate key behavioral factors affecting investor decisions in the Indian stock market” and converts it into a theoretical research article. Its purposes are fourfold: to organize the major behavioral factors into a coherent taxonomy; to assess their implications for BSE- and NSE-related investment decisions; to integrate financial literacy, experience, market stress, and digital information as boundary conditions; and to formulate propositions that can guide future empirical research. The article does not present invented primary data. Instead, it offers an original synthesis and testable conceptual model grounded in peer-reviewed research and current regulatory evidence.

## 2. Theoretical Foundations

### 2.1 Rational choice, market efficiency, and bounded rationality

Standard investment theory assumes purposeful choice under constraints. Investors are expected to use relevant information, estimate distributions of return, choose portfolios consistent with their risk preferences, and revise positions when new information changes expected value. This benchmark is useful because it defines decision quality in terms of consistency, diversification, cost awareness, and alignment with goals. Market efficiency further implies that publicly available opportunities are difficult to exploit systematically after costs. An investor who trades frequently on widely known information should therefore require a strong informational advantage to justify turnover.

Behavioral finance begins with a less demanding description of human capability. Simon's (1955) concept of bounded rationality recognizes that decision-makers have limited attention, time, computational capacity, and information-processing ability. Investors therefore use simplifying rules, or heuristics, to reduce a complex choice set. Heuristics can be adaptive when they save time and produce acceptable decisions, but they become biases when they create systematic and consequential error. In equity markets, the problem is acute because the investor must evaluate a very large set of securities, uncertain future cash flows, ambiguous news, changing macroeconomic conditions, and noisy social signals.

The relationship between efficiency and behavior is consequently two-sided. Efficient pricing can constrain the profitability of biased strategies, but biased demand can still affect trading volume, security selection, temporary mispricing, and volatility. Behavioral errors may cancel when they are independent, yet they may aggregate when investors attend to the same story, imitate the same visible traders, or respond asymmetrically to gains and losses. Limits to arbitrage can prevent rational traders from immediately eliminating such effects (Barberis et al., 1998; Daniel et al., 1998).

### 2.2 Prospect theory and reference-dependent choice

Prospect theory is the principal foundation for explaining investment decisions under gains and losses. Kahneman and Tversky (1979) showed that individuals evaluate outcomes relative to a reference point rather than solely in terms of final wealth. The value function is generally concave for gains, convex for losses, and steeper for losses than for equivalent gains. Investors may therefore become risk-averse after gains but risk-seeking when attempting to avoid or recover a loss. They also tend to overweight small probabilities and underweight moderate or high probabilities, which can encourage speculative demand for low-probability, high-payoff securities.

In practice, the purchase price often becomes the reference point. A fall below that price is coded as a loss even when the security remains appropriate in the portfolio, while a gain can create pressure to "lock in" success. This reference dependence underlies the disposition effect: the tendency to sell winners too early and hold losing positions too long (Odean, 1998; Shefrin & Statman, 1985). The consequence is not merely emotional discomfort. It can alter tax efficiency, portfolio risk, rebalancing, and the allocation of capital to superior alternatives.

### 2.3 Heuristics, self-attribution, and social learning

Tversky and Kahneman (1974) identified representativeness, availability, and anchoring as recurring heuristics in judgment under uncertainty. Investors use representativeness when they infer that a company with recent strong performance will continue to be a strong investment, even if the valuation already incorporates optimistic expectations. Availability causes memorable, vivid, or recently repeated information to receive excessive weight. Anchoring occurs when an initial number—such as an issue price, previous high, analyst target, or purchase price—continues to influence valuation despite new evidence.

Self-attribution adds a dynamic component. Investors may attribute successful outcomes to skill and unsuccessful outcomes to external events. This asymmetric learning raises confidence after favorable performance and can produce greater trading, concentration, and risk-taking. Daniel et al. (1998) connect overconfidence and biased self-attribution to underreaction and overreaction in security prices. Barber and Odean (2000, 2001) show that excessive trading associated with confidence can reduce net performance, while Statman et al. (2006) link marketwide trading volume to overconfidence.

Investment decisions are also social. Investors observe family, colleagues, financial influencers, market leaders, and price momentum. Social interaction can lower the perceived cost of participation and provide useful information, but it can also generate information cascades and herding. Scharfstein and Stein (1990) explain why professional decision-makers may imitate others to protect reputation, while Bikhchandani and Sharma (2000) distinguish intentional herding from correlated trading based on common information. Hong et al. (2004) show that social interaction is associated with stock-market participation, highlighting that social influence affects entry as well as security selection.

## 3. Review Design and Scope

This article adopts an integrative conceptual review rather than a statistical meta-analysis. The design is appropriate because the relevant literature combines experiments, surveys, brokerage records, return-based herding tests, structural-equation models, and qualitative studies. These designs measure different outcomes and cannot be pooled without imposing questionable equivalence. The review instead identifies recurring mechanisms, contrasts their observable implications, and develops a context-specific framework.

Candidate sources were located through publisher databases, indexed bibliographic records, reference chaining, and official regulatory publications. Priority was given to foundational theory, highly cited behavioral-finance evidence, systematic reviews, peer-reviewed Indian studies, and recent work on financial literacy, digital information, sentiment, and market participation. Studies were included when they directly addressed individual investment choice, trading behavior, portfolio selection, risk perception, or aggregate behavior with a clear behavioral interpretation. Pure price-forecasting studies and non-scholarly investment advice were excluded. The synthesis covers classic contributions from 1955 onward, with particular emphasis on Indian evidence published after 2010 and current regulatory evidence through 2026.

The analysis proceeds at three levels. The first level identifies the psychological mechanism. The second maps the mechanism to a specific decision outcome—participation, selection, allocation, trading intensity, diversification, or realization. The third identifies moderators and amplifiers, including financial literacy, investment experience, market stress, digital-platform design, social-media exposure, and demographic context. This structure avoids treating every bias as an interchangeable predictor of a single undifferentiated decision variable.

## 4. Key Behavioral Factors Affecting Investment Decisions

### 4.1 Overconfidence and self-attribution

Overconfidence refers to excessive faith in the accuracy of one's knowledge, forecasts, or trading ability. It can appear as overestimation of skill, overprecision of probability judgments, or an exaggerated belief in one's relative ability. In equity investing, overconfidence is visible in high turnover, narrow portfolios, aggressive timing, underestimation of downside risk, and resistance to disconfirming evidence.

Brokerage-record evidence shows why the bias matters. Barber and Odean (2000) found that investors who traded most frequently earned lower net returns than less active investors, consistent with the proposition that perceived informational advantage often fails to cover transaction costs and timing errors. Their later work identified gender differences in trading consistent with greater overconfidence among men (Barber & Odean, 2001). Grinblatt and Keloharju (2001) further demonstrated that trading is influenced by past returns, tax considerations, investor characteristics, and behavioral tendencies rather than by new fundamental information alone.

Indian evidence supports the relevance of overconfidence but also cautions against treating it as uniform. Prosad et al. (2015) ranked overconfidence as the most prominent among the four biases examined in their Delhi-NCR sample. Mishra and Metilda (2015) found that investment experience, gender, and education were associated with overconfidence and self-attribution. Shukla et al. (2024) reported significant effects of overconfidence, representativeness, and herding on stock-trading decisions in North India. These findings imply that experience can have competing effects: it may improve knowledge and pattern recognition, yet favorable past outcomes can also strengthen the illusion of skill.

Overconfidence primarily affects decision intensity and portfolio structure. A confident investor is more likely to act on a private interpretation, trade repeatedly, hold fewer securities, and use complex products. It may also increase participation by reducing perceived barriers. Therefore, confidence should not be treated as wholly undesirable. Calibrated confidence helps investors enter the market and remain committed to long-term plans; miscalibrated confidence produces excessive activity. Future measurement should distinguish self-efficacy—belief that one can understand and execute a plan—from overprecision and illusion of control.

### 4.2 Loss aversion, disposition effect, and break-even behavior

Loss aversion describes the greater psychological impact of losses relative to equivalent gains. It affects initial participation, asset allocation, and selling behavior. Highly loss-averse households may avoid equities, underinvest relative to long-term goals, or exit after short-term volatility. Once invested, the same individual may become risk-seeking in a losing position because realizing the loss makes it certain and psychologically final.

The disposition effect is the most direct trading manifestation. Shefrin and Statman (1985) explained why investors realize gains quickly but postpone losses; Odean (1998) documented the pattern using account-level records. The behavior can be reinforced by anchoring to the purchase price, regret avoidance, and the belief that a fallen stock is "due" to recover. Selling a winner provides pride and validates the original decision, whereas selling a loser requires acknowledging error.

In BSE and NSE portfolios, the effect should be studied at the trade level rather than only through survey agreement. Appropriate measures include the proportion of gains realized relative to the proportion of losses realized, holding periods of winners and losers, and the probability of sale as a function of unrealized return. Survey items can supplement these measures by capturing emotional discomfort and break-even goals, but transaction evidence is preferable because respondents may underreport behavior that appears irrational.

Loss aversion has ambiguous effects on decision quality. Caution can prevent leverage and speculative concentration, especially among inexperienced investors. However, extreme aversion can cause underparticipation, excessive cash holdings, panic selling after market declines, or failure to rebalance. The relevant policy goal is therefore not to eliminate sensitivity to loss but to align it with investment horizon, capacity for loss, and portfolio-level risk.

### 4.3 Herding, social proof, and information cascades

Herding occurs when investors follow the observed or inferred actions of others rather than relying primarily on private information. It may be rational when others possess superior information, reputationally defensive when deviation is costly, or behavioral when social proof substitutes for analysis. In retail markets, visible price momentum, trading-volume rankings, online discussion, influencer recommendations, and peer success stories can all create perceived consensus.

Market-level tests of herding commonly examine whether cross-sectional return dispersion falls during large market movements. Chang et al. (2000) developed a nonlinear dispersion approach that has been widely applied across countries. Evidence for India is conditional. Lao and Singh (2011) found herding in India during rising markets, while Ansari and Ansari (2021) reported that broad herding was not pervasive but emerged under particular liquidity or sentiment conditions. This variation is theoretically reasonable: imitation should intensify when uncertainty is high, private signals are weak, and a visible narrative dominates.

Herding affects security selection and timing. It directs attention to stocks already experiencing price and volume pressure, reduces independent analysis, and can produce crowded entry and synchronized exit. Yet all correlated trading is not irrational. Index rebalancing, common macroeconomic news, and institutional mandates may cause investors to trade in the same direction without imitation. Empirical studies should therefore combine return-dispersion measures with survey or transaction evidence on information sources and the sequence of decisions.

The Indian digital ecosystem makes social influence especially salient. SEBI's Investor Survey 2025 indicates that digital channels are central to awareness and that many investors rely to some extent on financial influencers when making decisions (SEBI, 2026). Such sources can improve accessibility and simplify complex concepts, but they can also amplify salience, confidence, and herd behavior. The key distinction is whether social information is independently verified and incorporated into a diversified plan or used as a substitute for suitability assessment.

**4.4 Anchoring and insufficient adjustment**

Anchoring occurs when an initial value exerts persistent influence on later judgment. Common investment anchors include the purchase price, a previous market high, an initial public offering price, a round-number index level, an analyst target, a broker recommendation, or a recently observed price. After new information arrives, investors adjust away from the anchor but often not enough.

Anchoring can affect valuation and exit. An investor may view a stock trading below its previous high as cheap even when earnings prospects have deteriorated. Another may refuse to sell below the purchase price because the original price has become a target rather than a historical fact. Anchors can also arise from public narratives—for example, a widely repeated target price can shape expectations even when it is based on outdated assumptions.

Anchoring is difficult to measure with general survey items because the bias is reference-specific. Stronger designs should present experimentally varied anchors, compare investor valuations before and after corrective information, or reconstruct the reference points visible at the time of a trade. It should also be modeled jointly with the disposition effect, because purchase-price anchoring is one mechanism that converts an unrealized loss into delayed realization.

**4.5 Representativeness, extrapolation, and recency**

Representativeness is the tendency to judge an investment by its resemblance to a familiar category or recent pattern while neglecting base rates and valuation. Investors may infer that a firm with strong recent earnings, a prominent brand, or an exciting sector theme is necessarily a superior stock. The inference confuses a good company with a good investment and overlooks the price already paid for expected growth.

Recency is closely related. Recent returns and news receive more weight than older but relevant evidence, producing trend extrapolation. De Bondt and Thaler (1985) showed that extreme past winners and losers can subsequently reverse, a result consistent with overreaction. Barberis et al. (1998) and Daniel et al. (1998) provide models in which representativeness, conservatism, and confidence contribute to momentum and reversal patterns.

For retail investors, representativeness often combines with attention. A stock that has delivered several visible gains becomes both salient and seemingly representative of a winner. The investor then interprets short-run success as evidence of persistent quality. This mechanism can increase entry after price appreciation, reduce valuation discipline, and generate sector concentration. In Indian research, representativeness appears repeatedly among the measured dimensions of investor bias (Jain et al., 2020; Jain et al., 2022; Shukla et al., 2024).

**4.6 Availability, attention, and information overload**

Availability causes judgments to depend on information that is easy to recall or retrieve. In a market with thousands of listed securities, attention is a scarce resource. Barber and Odean (2008) found that individual investors are net buyers of attention-grabbing stocks—those in the news, with extreme returns, or with unusually high volume. Da et al. (2011) later used internet search intensity as a direct proxy for investor attention.

Digital access changes the form rather than the existence of the constraint. Investors can obtain more information than before, but they cannot process all of it. Ranking screens, alerts, trending lists, push notifications, and short videos determine what enters the consideration set. As a result, platform architecture can influence selection even without giving explicit advice. Repeated exposure can also create familiarity and perceived credibility.

Information overload may produce either action or avoidance. Some investors trade the most salient idea without adequate verification; others postpone participation because the choice set appears complex. SEBI (2026) identifies complexity, information gaps, risk-return concerns, and trust as major barriers among non-investors. This suggests that investor education should emphasize information triage—how to identify decision-relevant data—rather than simply increasing the volume of content.

**4.7 Mental accounting and portfolio fragmentation**

Mental accounting refers to the tendency to assign money and investments to separate psychological accounts rather than evaluating total wealth and portfolio risk (Thaler, 1985, 1999). An investor may treat salary savings as safe capital, trading profits as "house money," and bonus income as available for speculation. Securities may also be evaluated one by one rather than as contributors to portfolio-level exposure.

This compartmentalization can undermine diversification. Holding several stocks may appear diversified even when they are concentrated in the same sector, factor, promoter group, or macroeconomic risk. An investor may tolerate high risk in a small "trading account" without considering its correlation with employment income or other assets. Conversely, mental accounts can support discipline when they separate emergency funds, retirement investments, and short-term goals. The behavioral issue is not categorization itself but the failure to recognize interactions across accounts.

Indian scale-development research identifies mental accounting as a distinct and measurable dimension of investor decision-making (Jain et al., 2020; Jain et al., 2022). Future BSE-NSE studies should therefore assess portfolio-level concentration, correlation, goal alignment, and cross-account rebalancing rather than relying only on the number of securities held.

**4.8 Familiarity, home preference, and perceived competence**

Familiarity bias leads investors to prefer securities, sectors, brands, locations, or business models they recognize. Familiarity can reduce perceived uncertainty and encourage participation, but it is not equivalent to informational advantage. Employees may overinvest in their employer, residents may favor local companies, and consumers may infer investment quality from product experience.

In India, familiarity may operate through nationally visible business groups, regionally dominant firms, public-sector enterprises, or sectors connected to the investor's occupation. The bias can produce concentrated portfolios and underexposure to unfamiliar but diversifying assets. It can also interact with trust: familiar names may be perceived as safer, even when their market risk or valuation is high.

Measurement should distinguish objective knowledge from subjective familiarity. An investor may know more about a local firm, in which case concentration could reflect information. Bias exists when perceived competence exceeds actual informational advantage or when familiarity is used as a proxy for safety without adequate analysis.

**4.9 Regret aversion, status quo, and inaction**

Regret is the anticipated or experienced pain of discovering that another choice would have produced a better outcome. Regret aversion can discourage participation because an investor fears making a visible mistake. It can also encourage inaction, delayed selling, and imitation: a decision shared with the crowd may feel less personally blameworthy than an independent decision.

The bias has a temporal dimension. Before investment, anticipated regret can favor familiar and conservative choices. After investment, realized or anticipated regret can lead investors to avoid reviewing a poor position or to double down in order to restore the original decision. Regret therefore connects loss aversion, anchoring, herding, and escalation of commitment.

Decision processes can reduce regret without eliminating accountability. Predefined review dates, written investment theses, exit criteria, and portfolio-level performance attribution allow investors to evaluate whether the process was reasonable even when the outcome was unfavorable. This shifts evaluation from hindsight to ex ante decision quality.

**4.10 Financial literacy, risk perception, and investor capability**

Financial literacy is not itself a behavioral bias, but it shapes how biases affect decisions. Investors who understand diversification, compounding, inflation, valuation, and the risk-return trade-off are better equipped to interpret market information and recognize misleading patterns. Van Rooij et al. (2011) showed that financial literacy is strongly associated with stock-market participation. Indian evidence similarly suggests that knowledge and awareness influence participation and decision quality.

However, literacy does not guarantee immunity. Knowledgeable investors can remain overconfident, and experience can reinforce self-attribution. The appropriate expectation is moderation rather than elimination. Adil et al. (2021) found that financial literacy moderated relationships between behavioral biases and investment decisions, and Gupta et al. (2025) reported a comparable moderating role among Indian retail investors. Saivasan and Lokhande (2022) further emphasize the interaction of risk propensity, behavioral biases, demographic factors, and risk perception.

Risk perception is the immediate channel through which many biases translate into action. Familiarity can reduce perceived risk, vivid losses can increase it, recent gains can suppress it, and social consensus can create false reassurance. A strong empirical model should therefore distinguish objective risk exposure, subjective risk perception, risk tolerance, and capacity for loss.

**Table 1**
**Behavioral Factors, Decision Channels, and Observable Manifestations**

| Behavioral factor | Core mechanism | Primary decision channel | Observable manifestation |
|---|---|---|---|
| Overconfidence | Excessive belief in knowledge or skill | Trading intensity, position size, concentration | High turnover; aggressive timing; narrow portfolios |
| Loss aversion / disposition | Losses loom larger than gains; reference dependence | Participation and sell/hold decisions | Early sale of winners; delayed realization of losses |
| Herding | Imitation or reliance on perceived consensus | Stock selection and synchronized timing | Buying popular stocks; clustered entry and exit |
| Anchoring | Insufficient adjustment from an initial value | Valuation and exit targets | Fixation on purchase price, prior high, or target price |
| Representativeness / recency | Extrapolation from recent or salient patterns | Expected return and sector selection | Chasing recent winners; neglect of base rates and valuation |
| Availability / attention | Overweighting easy-to-recall information | Consideration set and buying | Trading newsworthy, trending, or high-volume stocks |
| Mental accounting | Separating wealth into psychological accounts | Allocation and portfolio construction | Fragmented evaluation; hidden concentration across accounts |
| Familiarity | Preference for known firms, sectors, or regions | Security selection and diversification | Home, employer, brand, or sector concentration |
| Regret aversion | Avoidance of responsibility for a poor choice | Participation, review, and exit | Inaction; crowd-following; delayed correction |
| Financial capability | Knowledge and skill affecting information use | All stages | Better diversification and cost awareness, but possible confidence inflation |

Note. The factors are analytically distinct but often co-occur. Observable manifestations should be measured with transaction records or experimental tasks where feasible, rather than inferred solely from self-reported agreement.

## 5. Indian Market Context: Why Behavioral Effects May Differ across BSE and NSE Investors

The BSE and NSE operate within the same national regulatory and macroeconomic environment, and many companies are listed on both exchanges. Therefore, a simple comparison of exchange labels may not capture meaningful behavioral differences. The more relevant comparison is between investor segments, securities, and trading environments associated with each exchange: large-cap versus small-cap attention, cash versus derivatives participation, liquidity conditions, broker interfaces, regional access, and the information channels through which investors arrive at a decision.

India's investor base is heterogeneous. SEBI's Investor Survey 2025 estimates that 63% of households are aware of at least one securities-market product, while only 9.5% participate and 8.5% report holding a demat account. Among investor households, 40% are classified as dormant. Participation differs by gender, education, occupation, income, and generation, and the survey reports a strong preference for capital preservation (SEBI, 2026). These figures imply several distinct behavioral problems: non-participation despite awareness, entry without sustained engagement, and active participation with low tolerance for loss.

Digital intermediation can reduce transaction costs and informational barriers, but it also compresses the time between attention and action. A notification, social-media post, price alert, or trending list can lead directly to an order. This architecture strengthens the possible effect of availability, recency, herding, and overconfidence. It may be especially influential among new investors who have limited experience distinguishing market-wide movement, firm-specific information, and promotional content.

Market conditions also matter. During calm periods, investors may rely on valuation and long-term goals; during sharp rallies, representativeness and fear of missing out can dominate; during declines, loss aversion, panic, and break-even behavior become more visible. Indian herding studies show that collective behavior varies with market direction, liquidity, sentiment, and crisis conditions (Ansari & Ansari, 2021; Lao & Singh, 2011). A valid BSE-NSE comparison should therefore use regime-sensitive methods rather than a single average coefficient.

Finally, the distinction between direct equity investors and mutual-fund investors is important. Nedumparambil and Bhandari (2022) found that Indian mutual-fund flows respond to relatively simple performance measures and are adversely affected by uncertainty. Direct investors face a broader stock-selection problem and may display stronger attention and familiarity effects. A comprehensive study should either separate these groups or model investment mode as a moderator.

## 6. Proposed Conceptual Framework and Research Propositions

The proposed framework treats investment decision-making as a sequence rather than a single outcome. Investor capability and context shape what information is noticed; heuristics and emotions shape interpretation; and the resulting perception of risk, return, control, and social validation shapes behavior. The principal outcomes are participation, security selection, allocation, trading frequency, diversification, holding period, and exit. Financial literacy, experience, demographic characteristics, market regime, and digital-platform exposure operate as moderators.

Figure 1 summarizes the logic. Information and market cues do not directly produce decisions. They pass through behavioral mechanisms. For example, a price increase becomes an investment signal when it is interpreted through recency or representativeness; an influencer recommendation becomes actionable when social proof and confidence outweigh independent verification; an unrealized loss becomes persistent when the purchase price anchors the investor and regret discourages realization.

**Figure 1**

**Conceptual Framework for Behavioral Investment Decision-Making**

| **Information and market cues** | → | **Behavioral mechanisms** | → | **Investment outcomes** |
|---|---|---|---|---|
| Prices, returns, disclosures, analyst views, social media, peers, platform prompts | | Overconfidence; loss aversion; herding; anchoring; representativeness; availability; mental accounting; familiarity; regret | | Participation; stock choice; allocation; turnover; diversification; holding; sale |
| Moderators: financial literacy, experience, risk tolerance, demographics, volatility, liquidity, digital exposure | | | | |

### 6.1 Propositions

**P1.** Overconfidence is positively associated with trading frequency, concentrated positions, and speculative timing; these relationships are stronger when recent portfolio performance is favorable.

**P2.** Loss aversion and purchase-price anchoring increase the probability of holding losing securities and reduce the probability of realizing losses relative to gains.

**P3.** Herding has a stronger positive effect on attention-driven stock selection during high-sentiment, high-volatility, or high-liquidity market regimes than during normal regimes.

**P4.** Representativeness and recency increase expected-return extrapolation and the purchase of recent winners, particularly when investors rely on short-horizon performance displays.

**P5.** Mental accounting and familiarity are positively associated with hidden portfolio concentration and negatively associated with portfolio-level diversification.

**P6.** Exposure to social-media recommendations, influencer content, and platform salience cues strengthens the effects of availability, herding, and overconfidence on investment action.

**P7.** Financial literacy weakens the adverse effects of loss aversion, herding, anchoring, and mental accounting on decision quality, but investment experience may strengthen overconfidence through self-attribution.

**P8.** The relationship between behavioral factors and investment decisions differs more across investor segment, security liquidity, product type, and market regime than by exchange label alone.

### 6.2 Suggested empirical operationalization

The framework can be tested with a multi-method design. A structured survey can measure latent biases, financial literacy, risk tolerance, information sources, and self-reported decision practices. Confirmatory factor analysis should verify whether the behavioral constructs are distinct, particularly where anchoring, loss aversion, regret, and the disposition effect overlap. Structural-equation modeling can then examine direct, mediated, and moderated relationships.

Survey evidence should be complemented with objective behavior. Broker or investor-provided transaction histories can generate turnover, holding period, concentration, realized-gain and realized-loss ratios, and momentum-chasing measures. Market-level herding can be assessed through cross-sectional absolute deviation, but the interpretation should be supported by investor-level evidence because low dispersion can arise from common information. Experimental tasks can manipulate anchors, framing, social consensus, and platform displays to establish causality.

A comparative BSE-NSE design should classify observations by where the trade was executed, the primary exchange of the security, market capitalization, liquidity, sector, cash or derivative product, investor experience, and broker platform. Panel or diary data would be superior to a one-time survey because behavioral responses change after gains, losses, and volatility shocks. Multilevel models could separate within-investor change from between-investor differences.

**Table 2**
**Recommended Measures for Future Empirical Testing**

| Construct | Survey/experimental measure | Behavioral or market measure | Recommended analysis |
|---|---|---|---|
| Overconfidence | Calibration, relative-skill, illusion-of-control items | Turnover, concentration, forecast error | CFA/SEM; panel regression |
| Disposition effect | Loss discomfort and break-even items | PGR–PLR; sale hazard by unrealized return | Logit/survival models |
| Herding | Reliance on peers, influencers, market consensus | CSAD/CSSD; correlated order flow | Regime/quantile models |
| Anchoring | Experimental price or target anchors | Exit around purchase price or prior high | Randomized experiment; hazard model |
| Attention/recency | Information-source frequency and recall | Search intensity; news, volume, extreme return | Event study; panel regression |
| Mental accounting/familiarity | Separate-account and familiarity scales | Sector/employer/local concentration | Portfolio diagnostics; SEM |

| | | | |
|---|---|---|---|
| Financial literacy | Objective knowledge and numeracy items | Diversification, fee awareness, product suitability | Moderated mediation |

## 7. Discussion

The synthesis supports four broad conclusions. First, behavioral influences are not peripheral errors that appear only among uninformed investors. They are recurring responses to uncertainty, complexity, social information, and feedback. Expertise and experience change their form but do not necessarily remove them. This explains why investor education must address both knowledge and decision process.

Second, the same behavioral factor can produce both participation and harm. Confidence can help an individual overcome inertia but can later cause excessive trading. Familiarity can make a complex market approachable but can create concentration. Loss sensitivity can restrain leverage but can also prevent long-horizon equity participation. Policy and advisory practice should therefore seek calibration rather than the unrealistic elimination of emotion and heuristics.

Third, behaviors interact. A trending stock receives attention; recent gains create representativeness; peer discussion supplies social proof; successful early trades generate self-attribution; and a later decline activates anchoring and loss aversion. Treating these as independent predictors may understate the mechanism. Future empirical work should test clusters, sequences, and mediated pathways rather than only additive direct effects.

Fourth, market and platform context are part of investor behavior. Digital systems determine which securities are displayed, how returns are framed, how quickly an order can be placed, and whether portfolio-level risk is visible. Behavioral finance in India must therefore move beyond demographic profiling toward the joint study of investor psychology, market conditions, and interface design.

## 8. Implications

### 8.1 Implications for individual investors

Investors can improve decision quality by separating process from outcome. A profitable trade may result from luck, while a loss can follow a sound process. A written investment thesis should identify the reason for purchase, valuation or risk assumptions, expected holding period, position-size limit, and conditions that would invalidate the thesis. This record reduces hindsight and self-attribution.

Portfolio review should occur at the total-wealth level. Investors should examine sector, factor, promoter-group, and employer-income concentration across all accounts. Rebalancing rules, maximum position sizes, and predefined review dates can reduce disposition, familiarity, and mental-accounting effects. A cooling-off period before large or first-time speculative trades can reduce attention-driven action.

Information discipline is equally important. Investors should distinguish regulatory disclosures and audited information from commentary, verify recommendations through independent sources, and evaluate whether a stock is suitable for the portfolio rather than merely popular. Limiting frequent performance checks can reduce recency, loss salience, and impulsive trading.

### 8.2 Implications for advisors and intermediaries

Suitability assessment should include behavioral diagnostics in addition to age, income, and stated risk tolerance. Advisors can ask how clients respond to unrealized losses, whether they concentrate in familiar sectors, how often they trade after news, and which information sources they trust. The purpose is not to label clients as irrational but to design guardrails consistent with their predictable vulnerabilities.

Broker platforms can present portfolio-level concentration, turnover, realized and unrealized outcomes, and long-horizon return information. Alerts could identify repeated trading, oversized positions, or a sale decision driven mainly by a prior price. Interface experiments should test whether friction, neutral framing, and verification prompts improve outcomes without preventing legitimate execution.

### 8.3 Implications for SEBI, exchanges, and investor education

The gap between awareness and participation reported by SEBI (2026) suggests that disclosure and awareness campaigns should be supplemented by capability-building. Modules should teach base-rate reasoning, diversification, transaction-cost awareness, fraud and promotion detection, and the difference between a company narrative and an investment valuation. Education should be segmented for non-investors, new investors, active traders, and dormant investors because their behavioral barriers differ.

Regulatory communication can use behavioral insights ethically. Risk warnings should be specific, salient, and linked to the decision being made. Standardized performance presentation should include appropriate horizons and benchmarks to reduce selective recency. Influencer-related investor protection should focus on disclosure of incentives, verifiability of claims, and the boundary between education and personalized recommendation.

Exchanges and regulators can facilitate privacy-preserving research using de-identified transaction data. Such data would allow researchers to test turnover, disposition, concentration, and response to volatility across demographic and regional groups more accurately than self-report surveys. Collaboration with academic institutions could produce periodic behavioral-risk dashboards alongside conventional market-quality indicators.

## 9. Limitations and Future Research

This article is theoretical and does not estimate the prevalence or causal effect of any bias in the full Indian investor population. The reviewed evidence uses different samples, instruments, and market periods. Regional survey findings should not be generalized mechanically to all BSE and NSE participants. The conceptual framework therefore requires empirical validation.

Future research should prioritize longitudinal and transaction-linked designs. Investor diaries combined with brokerage records can reveal how confidence, attention, and risk perception change after gains and losses. Field experiments can test whether cooling-off prompts, portfolio-level concentration displays, or alternative performance frames improve decisions. Natural experiments based on platform changes, regulatory interventions, or market disruptions can provide stronger causal identification.

Research should also examine heterogeneity. New app-based investors, women investors, senior citizens, derivatives traders, mutual-fund investors, and investors outside major metropolitan areas may face different information environments and behavioral constraints. Language, regional networks, and trust in institutions could influence how social information is processed. Comparative studies should use measurement-invariance tests before concluding that a bias has the same meaning across groups.

Finally, future studies should connect investor behavior to market efficiency without assuming a one-way relationship. Inefficiency or volatility may activate behavioral responses, while synchronized biased behavior may contribute to price pressure. Dynamic models—panel vector autoregression, regime-switching models, quantile methods, and agent-based simulations—can examine this feedback over time.

## 10. Conclusion

This article converts the objective of identifying and evaluating behavioral factors in the Indian stock market into a theoretical research framework for BSE and NSE investors. The review shows that overconfidence, loss aversion, the disposition effect, herding, anchoring, representativeness, availability, mental accounting, familiarity, and regret aversion influence different stages of the investment process. Their effects are conditioned by financial capability, experience, risk perception, social information, market regimes, and platform design.

The practical implication is clear: better investment decisions require more than more information. Investors need calibrated confidence, portfolio-level thinking, disciplined review rules, and the ability to evaluate salient and social signals. Advisors, brokers, exchanges, and regulators can support these capabilities through behavioral suitability assessment, transparent interfaces, targeted education, and access to research-quality data. The proposed framework and propositions provide a basis for a rigorous empirical article using Indian investor surveys, transaction records, experiments, or mixed methods.

**References**

1. Adil, M., Singh, Y., & Ansari, M. S. (2021). How financial literacy moderates the association between behavioural biases and investment decision. Asian Journal of Accounting Research, 7(1), 17–30. https://doi.org/10.1108/AJAR-09-2020-0086
2. Ansari, A., & Ansari, V. A. (2021). Do investors herd in emerging economies? Evidence from the Indian equity market. Managerial Finance, 47(7), 951–974. https://doi.org/10.1108/MF-06-2020-0331
3. Badola, S., Sahu, A. K., & Adlakha, A. (2023). A systematic review on behavioral biases affecting individual investment decisions. Qualitative Research in Financial Markets, 16(3), 448–476. https://doi.org/10.1108/QRFM-05-2022-0095
4. Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. The Journal of Finance, 55(2), 773–806. https://doi.org/10.1111/0022-1082.00226
5. Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. The Quarterly Journal of Economics, 116(1), 261–292. https://doi.org/10.1162/003355301556400
6. Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. The Review of Financial Studies, 21(2), 785–818. https://doi.org/10.1093/rfs/hhm079
7. 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
8. Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), Handbook of the economics of finance (Vol. 1B, pp. 1053–1128). Elsevier. https://doi.org/10.1016/S1574-0102(03)01027-6
9. Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. IMF Staff Papers, 47(3), 279–310. https://doi.org/10.2307/3867650
10. Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. Journal of Banking & Finance, 24(10), 1651–1679. https://doi.org/10.1016/S0378-4266(99)00096-5
11. Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. The Journal of Finance, 66(5), 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x
12. Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. The Journal of Finance, 53(6), 1839–1885. https://doi.org/10.1111/0022-1082.00077
13. Das, A. R., & Panja, S. (2022). An empirical investigation on the influence of behavioural factors on investment decision making. Vision: The Journal of Business Perspective. Advance online publication. https://doi.org/10.1177/09722629221131101
14. De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? The Journal of Finance, 40(3), 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

15. Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383–417. https://doi.org/10.2307/2325486
16. Grinblatt, M., & Keloharju, M. (2001). What makes investors trade? The Journal of Finance, 56(2), 589–616. https://doi.org/10.1111/0022-1082.00338
17. Gupta, N., Rana, R., & Tandon, D. (2025). Financial literacy as a moderator in behavioral biases and investor decisions. Indian Journal of Finance, 19(5), 79–94. https://doi.org/10.17010/ijf/2025/v19i5/175045
18. Haritha, P. H., & Uchil, R. (2020). Impact of investor sentiment on decision-making in Indian stock market: An empirical analysis. Journal of Advances in Management Research, 17(1), 66–83. https://doi.org/10.1108/JAMR-03-2019-0041
19. Hirshleifer, D. (2001). Investor psychology and asset pricing. The Journal of Finance, 56(4), 1533–1597. https://doi.org/10.1111/0022-1082.00379
20. Hong, H., Kubik, J. D., & Stein, J. C. (2004). Social interaction and stock-market participation. The Journal of Finance, 59(1), 137–163. https://doi.org/10.1111/j.1540-6261.2004.00629.x
21. Jain, J., Walia, N., & Gupta, S. (2020). Evaluation of behavioral biases affecting investment decision making of individual equity investors by fuzzy analytic hierarchy process. Review of Behavioral Finance, 12(3), 297–314. https://doi.org/10.1108/RBF-03-2019-0044
22. Jain, J., Walia, N., Kaur, M., & Singh, S. (2022). Behavioural biases affecting investors' decision-making process: A scale development approach. Management Research Review, 45(8), 1079–1098. https://doi.org/10.1108/MRR-02-2021-0139
23. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–292. https://doi.org/10.2307/1914185
24. Kumar, S., & Goyal, N. (2015). Behavioural biases in investment decision making—A systematic literature review. Qualitative Research in Financial Markets, 7(1), 88–108. https://doi.org/10.1108/QRFM-07-2014-0022
25. Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. Journal of Asian Economics, 22(6), 495–506. https://doi.org/10.1016/j.asieco.2011.08.001
26. Malmendier, U., & Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? The Quarterly Journal of Economics, 126(1), 373–416. https://doi.org/10.1093/qje/qjq004
27. Mishra, K. C., & Metilda, M. J. (2015). A study on the impact of investment experience, gender, and level of education on overconfidence and self-attribution bias. IIMB Management Review, 27(4), 228–239. https://doi.org/10.1016/j.iimb.2015.09.001
28. Nedumparambil, E., & Bhandari, A. K. (2022). Risk factors, uncertainty, and investment decision: Evidence from mutual fund flows from India. Indian Economic Review, 57, 349–372. https://doi.org/10.1007/s41775-022-00155-8
29. Odean, T. (1998). Are investors reluctant to realize their losses? The Journal of Finance, 53(5), 1775–1798. https://doi.org/10.1111/0022-1082.00072
30. Paul, H. I. S., & Sundaram, N. (2023). Behavioral biases and their influence on investment decision-making: A systematic literature review and future research agenda. Journal of Law and Sustainable Development, 11(4), e904. https://doi.org/10.55908/sdgs.v11i4.904
31. Prosad, J. M., Kapoor, S., & Sengupta, J. (2015). Behavioral biases of Indian investors: A survey of Delhi-NCR region. Qualitative Research in Financial Markets, 7(3), 230–263. https://doi.org/10.1108/QRFM-04-2014-0012

32. Raut, R. K., Das, N., & Mishra, R. (2020). Behaviour of individual investors in stock market trading: Evidence from India. Global Business Review, 21(3), 818–833. https://doi.org/10.1177/0972150918778915
33. Saivasan, R., & Lokhande, M. (2022). Influence of risk propensity, behavioural biases and demographic factors on equity investors' risk perception. Asian Journal of Economics and Banking, 6(3), 373–403. https://doi.org/10.1108/AJEB-06-2021-0074
34. Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. American Economic Review, 80(3), 465–479.
35. Securities and Exchange Board of India. (2026). SEBI Investor Survey 2025: Main report.
36. Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. The Journal of Finance, 40(3), 777–790. https://doi.org/10.1111/j.1540-6261.1985.tb05002.x
37. Shukla, A., Dadhich, M., Vaya, D., & Goel, A. (2024). Impact of behavioral biases on investors' stock trading decisions: A comprehensive quantitative analysis. Indian Journal of Science and Technology, 17(8), 670–678. https://doi.org/10.17485/IJST/v17i8.2845
38. Sias, R. W. (2004). Institutional herding. The Review of Financial Studies, 17(1), 165–206. https://doi.org/10.1093/rfs/hhg035
39. Simon, H. A. (1955). A behavioral model of rational choice. The Quarterly Journal of Economics, 69(1), 99–118. https://doi.org/10.2307/1884852
40. Statman, M., Thorley, S., & Vorkink, K. (2006). Investor overconfidence and trading volume. The Review of Financial Studies, 19(4), 1531–1565. https://doi.org/10.1093/rfs/hhj032
41. Thaler, R. (1985). Mental accounting and consumer choice. Marketing Science, 4(3), 199–214. https://doi.org/10.1287/mksc.4.3.199
42. Thaler, R. H. (1999). Mental accounting matters. Journal of Behavioral Decision Making, 12(3), 183–206. https://doi.org/10.1002/(SICI)1099-0771(199909)12:3<183::AID-BDM318>3.0.CO;2-F
43. 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
44. Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. Journal of Financial Economics, 101(2), 449–472. https://doi.org/10.1016/j.jfineco.2011.03.006
45. Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. Qualitative Research in Financial Markets, 10(2), 210–251. https://doi.org/10.1108/QRFM-04-2017-0028


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