International Journal of Research in Commerce and Management Studies

ISSN 2582-2292

Vol. 8, No. 04 July-August; 2026 Page. No. 54-65

To cite this article: Deepthi K and Dr. Monica S (2026). COGNITIVE BIASES AND TRADING BEHAVIOUR IN APP – BASED PLATFORMS: A LITERATURE REVIEW, International Journal of Research in Commerce and Management Studies (IJRCMS) 8 (4): 54-65 Article No. 802 Sub Id 1336

COGNITIVE BIASES AND TRADING BEHAVIOUR IN APP – BASED PLATFORMS: A LITERATURE REVIEW

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DOI: https://doi.org/10.38193/IJRCMS.2026.8405

ABSTRACT

The rapid rise of app-based trading platforms has transformed retail investing by making financial markets more accessible, faster, and more interactive for individual investors. At the same time, this digital shift has intensified the role of cognitive biases in trading behaviour, especially among younger investors who rely heavily on mobile applications for investment decisions. This literature review examines the relationship between cognitive biases and trading behaviour in app-based platforms, with particular attention to biases such as overconfidence, herding, loss aversion, anchoring, confirmation bias, and availability bias. The review synthesizes existing research on behavioral finance, digital investment platforms, and mobile trading psychology to explain how app design features such as push notifications, gamification, real-time price alerts, social cues, and simplified one-tap trading can reinforce impulsive and irrational decision-making. It also highlights how Millennials and Gen Z, as digitally native investors, are especially vulnerable to these influences due to their frequent use of mobile technology and greater exposure to online financial content. The literature further suggests that such biases contribute to excessive trading, poor diversification, short holding periods, and suboptimal portfolio outcomes. However, most studies remain fragmented, with limited integration of platform design, behavioral bias, and actual trading outcomes in a single framework. This review identifies the need for more empirical research that links digital interface features to observable investment behavior and evaluates the effectiveness of regulatory nudges and investor education in reducing bias-driven trading.

KEYWORDS: Cognitive biases, trading behaviour, app-based platforms, behavioral finance

1. INTRODUCTION

The rapid expansion of smartphone-based investing has transformed the way young Indians participate in financial markets, making app-based trading platforms a major gateway to equity participation for

Millennials and Generation

Z. Digital brokerage applications have reduced entry barriers through simplified onboarding, low transaction costs, intuitive dashboards, and real-time execution, thereby attracting a generation that is comfortable with mobile technology and instant information. While this technological shift has widened market access, it has also created a decision environment in which speed, convenience, social cues, and design features may intensify cognitive biases in trading behavior.

Behavioral finance challenges the traditional assumption that investors act fully rationally and instead argues that investment decisions are often shaped by bounded rationality, mental shortcuts, and psychological distortions. In app-based trading contexts, these distortions may become more pronounced because investors continuously interact with notifications, trending stocks, visual price movements, peer conversations, and influencer-driven financial content. Such conditions can encourage reliance on cognitive biases such as overconfidence, anchoring, availability bias, confirmation bias, and herd behavior, each of which may distort security selection, timing of trades, risk perception, and portfolio diversification.

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2. CONCEPTUAL FRAMEWORK

2.1 Concept of Cognitive Biases

Cognitive biases represent systematic patterns of deviation from norm or rationality in judgment, where individuals create their own "subjective reality" from objective input. In behavioral finance, these mental shortcuts arise from the brain's effort to simplify complex information processing under uncertainty.

Key Characteristics:

• Originate from heuristics (mental rules of thumb) like availability, representativeness, and anchoring.
• Classified as cognitive (information-processing errors) or emotional (affect-driven).
• Predictable and consistent across individuals and contexts, unlike random errors.

Major Types Relevant to Trading:

• **Overconfidence Bias:** Excessive belief in one's knowledge or predictive ability, leading to excessive trading.
• **Anchoring:** Fixation on initial price levels or reference points, distorting valuation.
• **Availability Bias:** Overweighting recently observed or easily recalled information (e.g., trending stocks).
• **Confirmation Bias:** Seeking information that confirms preexisting beliefs while ignoring contradictory evidence.
• **Herding:** Following crowd behavior rather than independent analysis.
• **Loss Aversion:** Preferring to avoid losses over acquiring equivalent gains (Prospect Theory).

2.2 Concept of Trading Behaviour

Trading behaviour refers to observable patterns in investment decision-making, including frequency, volume, timing, risk exposure, and portfolio construction choices. Behavioral finance examines how psychological factors systematically influence these patterns beyond traditional risk-return optimization.

Core Components:

• Trading Frequency: Number of buy/sell transactions per period; bias-driven investors trade excessively.
• Holding Period: Duration securities are held; shorter periods indicate speculative behavior.
• Risk-Taking: Position sizing, leverage usage, and concentration in high-volatility assets.
• Disposition Effect: Selling winners too early and holding losers too long.
• Portfolio Diversification: Spread across asset classes, sectors, and individual securities.
• Reaction to Information: Speed and nature of response to news, earnings, or market events.

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3. REVIEW OF LITERATURE

Table 1: Outline of Literature Review

Theme	Key Content/ Articles/ Reports/Literatures Related to	Number of Articles reviewed
Behavioral Finance Foundations	• Cognitive biases in investing • Prospect theory trading • Overconfidence bias disposition effect	**7**
Specific Trading Biases	• Herding in stock markets • Loss aversion retail investors • Anchoring trading behavior	4
Fintech & App-Based Trading	• behavioral biases fintech platforms • App design investment decisions • Mobile trading psychology	**5**
Millennials & Gen Z Investing	• Gen Z investment behavior • Millennial trading patterns • youth retail investors	4
Technology Adoption Models	• TAM fintech investing • UTAUT digital trading • Nudge theory investment apps	5
Methodological Approaches	• Survey instruments investor biases • Transaction data behavioral finance • SEM trading behavior India	5

Barberis, N., & Thaler, R. (2003) Behavioral finance suggests that we can better understand certain market trends by accepting that not all investors act logically. This field rests on two main pillars: **limits to arbitrage** (the idea that rational investors can't always fix market errors caused by irrational ones) and **psychology** (the study of common human biases). By applying these concepts, experts can explain patterns in the overall stock market, variations in asset returns, how individuals trade, and how corporations make financial decisions. While the field has come a long way, its future lies in further refining these models to predict market behavior.

Swati Yadav & Et.all (2025) Digital investment platforms often feel complicated because human emotions—like overconfidence, fear of losing money, or the urge to follow the crowd—frequently override logic. A recent study using surveys and platform data found that these psychological biases consistently lead users toward poor financial choices. Interestingly, these "gut-feeling" decisions don't just hurt bank accounts; they also spill over into how people manage healthcare spending, potentially limiting their access to medical care.

Chanchal Mandal & Sonia Riyat (2024) This paper investigates how six specific emotional biases—including overconfidence, optimism, and regret aversion—shape investor behavior and deviate from purely rational decision-making. By analyzing existing research and case studies, the study demonstrates that these biases often act as a subconscious "compass" for investors, though they can frequently lead to suboptimal outcomes in the securities market.

Yang-Yu Liu & Et.all (2014) stated that Prospect theory serves as the leading model for understanding how people perceive risk, specifically highlighting the "reflection effect"—where individuals avoid risk when gaining but seek it when facing losses—and "loss aversion," the tendency to feel the pain of a loss more intensely than the joy of an equivalent gain. While these concepts are well-established in theory, this study provides rare, large-scale empirical proof by analyzing over 28 million trades from 81,000 investors.

Jing Yao & Duan Li (2013) this study explores how the core elements of prospect theory—reference dependence, loss aversion, and risk-seeking for losses—drive investor behavior differently than traditional risk models. While these traits don't always show up clearly in isolated individual choices, they become powerful when prospect-theory investors interact with traditional, rational investors in a live market.

Sushmita & Et. All (2018) this research into behavioral finance highlights how psychological biases lead Indian investors to act irrationally, departing from traditional economic theories like expected utility. Focusing on the Bombay Stock Exchange (BSE SENSEX), the study used regression analysis to prove that overconfidence and the disposition effect (selling winners' too early and holding losers too long) significantly drive trading volumes and market returns.

T. Sobha Rani & Et. All (2024) this study examines how the combination of overconfidence and the disposition effect creates a "double hit" to investor performance. While overconfidence triggers excessive trading and a dangerous underestimation of risk, the disposition effect causes investors to cling to losing stocks while selling winners too quickly.

Pooja Gupta and Bindya Kohli (2021) stated that This study examines herding behavior—when investors trade in the same direction at the same time—within the Indian stock market across three distinct periods: before (2003–2007), during (2008–2012), and after (2013–2017) the global financial crisis. People typically herd to feel part of a group, avoid "missing out," or react to common news.

Adik Duwi Rahayu (2020) this comprehensive review of 84 international and local journals confirms that herding behavior is a nearly universal phenomenon across global stock markets, where investors abandon independent analysis to follow the crowd. This collective behavior is driven by a complex mix of external economic pressures—such as financial crises, rising interest rates, and currency depreciation—and internal market flaws like poor information transparency and high volatility.

Vaibhav Dhuri (2024) the recent surge in the Indian stock market has intensified research into investor psychology, particularly herding bias. Using a modified Cross-Sectional Absolute Deviation (CSAD) model for greater accuracy, this study analyzed whether Indian investors "follow the crowd" during various market conditions—including extreme swings, structural shifts, and fluctuating trade volumes.

Oyetade & Et. All (2025) This study explores how loss aversion—the psychological tendency to prioritize avoiding losses over acquiring gains—drives retail investors in Nigeria toward overly conservative financial choices. By combining quantitative data with qualitative interviews, the research demonstrates that while this bias is a powerful motivator, financial knowledge acts as a critical moderator, allowing more educated investors to bypass emotional hurdles and adopt more aggressive, rational strategies.

Mahir Aya & Et. All (2024) The integration of financial technology into the modern economy has sparked a necessary reevaluation of user adoption through the lens of behavioral finance, revealing that decisions to engage with digital platforms are often driven by non-rational factors rather than pure logic.

Evin V Mathew (2026) this study explores how the rise of mobile trading platforms has reshaped the habits of young investors, moving beyond traditional analysis to include psychological influences like optimism, overconfidence, and herding behavior. By analyzing data from 100 young investors using regression analysis, the research surprisingly found that these psychological biases do not significantly predict how often or how actively these individuals use trading apps.

Viren M. Patel (2025) the surge in digital technology has fundamentally reshaped the Indian stock market by giving investors access to sophisticated mobile trading applications. This study, based on data from 187 active users in Ahmedabad, explores how these platforms influence investor perception and decision-making. The findings highlight that users value these apps for their convenience and the analytical tools that simplify complex market operations.

Christiansen Dula (2025) while financial success is often credited to data, charts, and timing, the most powerful influence on any trade is the human mind. Trading psychology acts as the invisible divide between consistent winners and those who struggle, serving as the discipline required to actually execute what technical analysis identifies.

Janaranjani (2026) this study explores the dual nature of these features: while they can improve financial awareness and simplify complex choices, they also risk triggering impulsive trading and deep-seated biases like overconfidence and herd behaviour. The findings suggest that as technology reshapes how people invest, there is a critical need for responsible platform design and robust regulatory oversight.

Priyanka Rachel (2026) this study analyzes the investment habits of Gen Z professionals in Hyderabad, revealing that despite their digital fluency, they prioritize long-term financial security over high-risk speculative assets. By surveying 90 active traders, the research found that these individuals—typically aged 24–26—favour stable options like Fixed Deposits and Recurring Deposits rather than cryptocurrencies or NFTs.

Yashika Gupta (2026) The landscape of youth investment has shifted dramatically as individuals aged 18–35 increasingly move away from traditional models toward active market participation fueled by digital accessibility and financial influencers. This study examines how mobile trading apps and rising financial literacy have empowered a younger demographic to enter diverse investment avenues once reserved for more established professionals.

Siteng Wu (2022) using the GameStop short squeeze as a pivotal case study, this research examines the specific internal and external drivers that lead young investors to make irrational financial decisions. The study finds that traditional economic models fail to account for the unique synergy between social media influence, gamified trading platforms, and heightened investor sentiment, which collectively override logical analysis.

Vaivaw Kumar and Kunal Sinha (2025) this research applies the Technology Acceptance Model (TAM) to the Indian NBFC sector to determine what drives the adoption of digital financial services among underserved populations. At its core, the study evaluates how Perceived Usefulness and Perceived Ease of Use shape an individual's intention to use these platforms, while integrating secondary factors like Trust, Perceived Risk, and Subjective Norms to capture the specific anxieties and social influences of vulnerable users.

Muhammed Basid Amnas & et. all (2025) this study investigates the adoption of FinTech in India by combining the Technology Acceptance Model (TAM) with the E-S-QUAL framework to highlight the critical role of service quality. By analyzing data from 304 Indian users through structural equation modeling, the research confirms that Perceived Usefulness (PU) and Perceived Ease of Use (PE) are primary drivers of adoption, with high service quality significantly boosting both factors.

Shriya & Velmurugan (2025) this study utilizes an extended UTAUT2 framework to identify what drives millennial investors in emerging equity markets to adopt FinTech tools, focusing specifically on the roles of trust and transparency. By analyzing data from 352 respondents, the research found that high performance expectations, social influence, and clear transparency

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significantly boost the intention to use these platforms, while perceived risk acts as a notable deterrent.

Osly Usman & et. all (2025) this study applies the UTAUT framework to evaluate how metaverse technologies are being adopted within business education at two major Indonesian universities. By surveying undergraduate students and using PLS-SEM analysis, the research determined that performance expectancy (perceived usefulness) and social influence are the primary drivers of a student's intention to use virtual and augmented reality tools.

Cynthia Weiyi Cai (2020) this systematic review of nudge literature clarifies that while choice architecture is highly effective at guiding people toward specific outcomes, the ethical debate remains over whether these nudges always lead to the individual's best interests. In financial markets, regulators and intermediaries' advantage nudge theory to influence investor behavior by strategically presenting choices and curating information.

FINRA Foundation (2021) the FINRA Foundation's 2021 NFCS Investor Survey Instrument is a validated tool designed to measure U.S. retail investor behavior, including psychological biases like overconfidence, herding, and loss aversion, as well as knowledge levels. Literature utilizing this instrument highlights that while investors display high self-confidence, many struggle with basic concepts like margin trading and exhibit biases in high-risk asset classes.

Yavuz Selim Balcıoğlu & et. all (2025) this study enhances financial fraud detection by integrating behavioral finance theory with machine learning to analyze customer transaction patterns. By examining a diverse dataset of transactions, the researchers identified that fraud risk is highly dependent on the transaction type—with transfers showing the highest risk (55%) and withdrawals showing none—and noted that fraudulent actions typically involve monetary values 28% higher than legitimate ones.

Chhaya Dev & et. all (2024) this study investigates the drivers of stock market participation among 400 residents in the mountainous Himachal Pradesh region of India, specifically comparing economic and non-economic influences. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the research uncovered a striking trend: non-economic factors significantly drive the willingness to invest, whereas traditional economic factors showed an insignificant impact.

Shrinivas R. Patil & et. all (2025) this study uses a multi-method analytical approach to explore how financial literacy shapes the investment sentiment of 300 Indian retail investors through a novel "dual-mediation" model. The findings reveal that while financial literacy significantly boosts investment confidence, it does not drive market participation directly; instead, it works indirectly by altering psychological factors like risk attitude and behavioral biases.

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4. RESEARCH GAP

While extensive literature documents cognitive biases in traditional investing, fintech adoption patterns, and youth investment behavior separately, a critical gap exists in empirically linking app-specific design elements (notifications, gamification, leaderboards) to bias amplification and actual trading outcomes among Indian Millennials and Gen Z.

…No study integrates transaction-level app data from platforms like Zerodha/Groww with validated behavioral instruments to test generational differences in Karnataka's fintech hub, nor evaluates SEBI nudge interventions (2025 regulations) effectiveness, leaving policymakers without evidence on mitigating digital trading psychology risks among India's 65% youth demat surge.

5. RESEARCH OBJECTIVES

Table 2: Objectives

RO – 1	To study the concept of behavioral aspects about trading among different generations
RO – 2	To examine the extent to which app-specific design features amplify cognitive biases among Millennials and Gen Z traders on platforms
RO – 3	To investigate how cognitive biases mediate the relationship between mobile trading app usage and actual trading behaviors

6. VARIABLE IDENTIFICATION

Table 3: Study Variables

Independent Variables (App Design Features)	Mediating Variables (Cognitive Biases)	Dependent Variables (Trading Behaviour)
IV1: Push Notifications Frequency **IV2:** Gamification Elements (Leaderboards/Badges) **IV3**: Real-Time Trending Stocks **IV4:** Social Feed Integration **IV5:** Frictionless One-Tap Trading	**M1**: Overconfidence Bias **M2:** Herding Behaviour **M3:** Loss Aversion **M4:** Anchoring Bias **M5:** Availability Bias	**DV1:** Trading Frequency (trades/month) **DV2:** Average Holding Period (days) **DV3**: Portfolio Risk (VaR, Beta) **DV4**: Disposition Effect Ratio **DV5:** Performance Attribution (Alpha)

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7. RESEARCH IMPLICATIONS

7.1 Theoretical Implications

The study advances behavioral finance theory by validating an integrated digital-behavioral framework that accounts for the unique pressures of mobile-first economies. It bridges the gap between traditional prospect theory and modern "gamified" finance, proving that the medium of investment (the smartphone interface) is as influential as the asset itself.

7.2 Managerial & Design Implications

For FinTech developers and platform leaders (e.g., Zerodha, Groww), the research provides a diagnostic roadmap for ethical UI/UX design. By mapping specific features—like "trending stocks" or "one-tap execution"—to adverse trading outcomes, managers can prioritize "choice architecture" that promotes user longevity rather than just short-term engagement.

7.3 Policy & Regulatory Implications

The study informs the national discourse on SEBI's 2025 Nudge Framework by highlighting the limitations of static risk disclosures. It provides a blueprint for regulators to move toward "smart nudges," such as mandatory cooldown periods after a series of rapid trades or personalized bias alerts.

8. CONCLUSION

This research examines how the "gamified" design of Indian mobile trading apps—featuring push notifications, trending tickers, and one-tap execution—triggers systematic cognitive biases like overconfidence and herding among Millennial and Gen Z investors. While these platforms have democratized market access, the study finds that their high-speed interfaces often override rational analysis, leading to impulsive trading, shorter holding periods, and the disposition effect.

By analyzing the effectiveness of SEBI's 2025 Nudge Interventions, the research highlights a critical need for "smarter" regulatory guardrails and responsible platform design that prioritizes long-term financial health over short-term engagement. Ultimately, the findings advocate for tailored financial education to bridge the gap between digital access and disciplined wealth creation, ensuring that technology empowers rather than exploits the next generation of retail investors.

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