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Research Article

A Study on Behavioral Biases Affecting Investment Decisions on Fintech Trading Platforms in Surat District

Dr. Chintan A. Shah[1] and Prof. Jaydip Chaudhari[2]
[1]Assistant Professor SDJ International College, Vesu Affiliated to Veer Narmad South Gujarat University, Surat.
[2]Professor Department of Business & Industrial Management, Veer Narmad South Gujarat University, Surat.
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***Corresponding author: Dr. Chintan A. Shah (*chintanshah.mba@gmail.com*)**

Abstract: The rapid expansion of FinTech trading platforms has transformed the investment landscape in India by providing easy and quick access to financial markets. In cities like Surat, a growing number of retail investors actively use digital platforms for trading and investment purposes. However, despite technological advancement, investors often make decisions influenced by psychological and emotional factors rather than rational analysis. This study aims to examine the behavioural biases affecting investment decisions on FinTech trading platforms in Surat District. The study is descriptive in nature and is based on primary data collected from 700 FinTech investors using a structured questionnaire. Secondary data was collected from journals, reports, and previous studies. Various statistical tools such as frequency analysis, descriptive statistics, normality tests, reliability analysis, correlation, t-test, ANOVA, and chi-square tests were applied for data analysis. The findings reveal that behavioural biases like overconfidence, herd behaviour, and loss aversion significantly influence investment decisions. Results also indicate that factors such as age, experience, and platform usage patterns play an important role in shaping investor behaviour. The study concludes that while FinTech platforms encourage greater participation in financial markets, they also increase the risk of biased decision-making. Understanding these biases can help investors make better choices, assist platforms in designing responsible systems, and support policymakers in improving investor protection. The study contributes valuable insights into behavioural finance in the context of digital trading.

Keywords: Behavioural Biases, FinTech Trading Platforms, Investment Decisions, Investor Behaviour, Surat District.

INTRODUCTION

In recent years, the Indian financial market has witnessed a rapid shift from traditional stockbroking methods to digital and mobile-based FinTech trading platforms. With the increasing use of smartphones, affordable internet access, and user-friendly trading applications, a large number of retail investors, especially young and first-time investors, have started participating in stock trading, mutual funds, cryptocurrencies, and other digital investment avenues. While these platforms provide convenience, speed, and real-time access to market information, investment decisions made on such platforms are not always rational or well-planned. Instead, they are often influenced by psychological and emotional factors known as behavioural biases. Behavioural finance challenges the traditional finance theory that assumes investors are fully rational and always aim to maximise returns. In reality, investors tend to rely on past experiences, emotions, market rumours, social media trends, and personal beliefs, which significantly affect their decision-making process. On FinTech trading platforms, where instant buying and selling are just a click away, the influence of behavioural biases becomes even stronger. Biases such as overconfidence, herd behaviour, loss aversion, anchoring, mental accounting, and confirmation bias frequently guide investors' actions, leading to impulsive trades, excessive risk-taking, or avoidance of profitable opportunities. Overconfidence bias, for instance, encourages investors to believe they possess superior market knowledge, resulting in frequent trading and underestimation of risks. Herd behaviour pushes investors to follow popular market trends or social media recommendations without proper analysis, often causing asset bubbles or panic selling. Similarly, loss aversion leads investors to hold on to losing investments for too long, hoping for recovery, while selling profitable assets too early. FinTech platforms, through features like push notifications, price alerts, gamified interfaces, and influencer-driven content, can unintentionally amplify these biases by creating urgency and emotional reactions. In the Indian context, where financial literacy levels vary widely and many investors enter the market with limited formal training, the impact of behavioural biases becomes even more critical. Cultural factors, peer influence, fear of missing out (FOMO), and trust in informal advice further shape investor behaviour on digital platforms. Understanding these behavioural biases is essential not only for individual investors but also for policymakers, FinTech companies, and regulators, as irrational decision-making can lead to financial losses, market instability, and reduced investor confidence. This study aims to examine the key behavioural biases affecting investment decisions on FinTech trading platforms, with a specific focus on how psychological factors interact with digital trading environments. By identifying the nature and intensity of these biases, the study seeks to provide valuable insights that can help investors make more informed decisions, assist FinTech platforms in designing responsible user

Name: Dr. Chintan A. Shah
Email: chintanshah.mba@gmail.com

interfaces, and support regulators in promoting investor protection and financial awareness. Overall, analysing behavioural biases in FinTech-based investing is crucial for ensuring sustainable participation in digital financial markets and encouraging healthier investment practices in the rapidly evolving Indian financial ecosystem.

LITERATURE REVIEW

Baker and Ricciardi (2014) reviewed psychological factors affecting financial planning and investment decisions. Using comprehensive literature review, they highlighted biases including myopic loss aversion, status quo bias, and mental accounting. Their findings suggest that investors often make inconsistent decisions when facing risk and reward choices. The analysis concluded that understanding intrinsic biases is key to improving investment behaviour. The study emphasized that education and structured guidance can reduce behavioural errors. It also noted that biased behaviour is common across age, gender, and experience levels. These insights are valuable for digital trading environments where split-second decisions are common.

Barber and Odean (2001) examined how overconfidence affects individual investors' trading behaviour in stock markets. They used historical trading data and statistical analysis to compare trading frequency and returns of different investor groups. The study found that overconfident investors trade more frequently, but this frequent trading often leads to lower net returns due to transaction costs and poor timing. The analysis showed that investors, especially males, tend to overestimate their skills, believing they can outperform the market. The study concluded that behavioural biases like overconfidence can negatively affect investment performance by encouraging excessive trading and risk-taking. This research highlights how investor psychology can lead to suboptimal financial decisions, emphasizing the need for awareness and education. The findings support the idea that rational decision-making is limited in real-world markets.

Chaffai and Medhioub (2018) explored herding behaviour in stock markets to understand how investors follow crowd actions instead of independent analysis. They used quantitative methods and market data analysis to measure the degree of herd behaviour. The study found significant evidence that investors tend to mimic others, especially during market volatility, leading to assets being overvalued or undervalued. The research concluded that herding can cause instability and reduce market efficiency. The findings are significant for FinTech environments where social proof, ratings, and trending stocks influence decisions. Herding was shown to be more pronounced among inexperienced investors. The study highlights the need for better guidance and tools to discourage blind following.

Daniel et al. (1998) studied how psychological biases influence security prices and market behaviour. They used theoretical modeling and empirical tests to understand how overreaction and underreaction emerge in financial markets. Their research found that investor sentiment and biased expectations can cause prices to deviate from fundamental values. Especially in digital trading environments, strong emotions and herd mentality can drive prices up or down rapidly. The conclusion emphasizes that markets are not always efficient because of behavioural influences. The study provided evidence that psychological biases directly affect pricing and returns in financial markets. It supports the broader field of behavioural finance by linking investor bias with market anomalies.

Glaser and Weber (2007) analysed the link between overconfidence and trading volume using empirical trading records of investors. They applied regression analysis to measure how confidence levels influence trade frequency. The findings revealed that overconfident investors trade more frequently and are less likely to diversify holdings. The study concluded that excessive trading arising from overconfidence does not always lead to better performance. It underlined that investors with overestimated abilities can incur higher losses and increased costs. The research suggests that recognising personal bias is important for better investment decisions. It supports the idea that behavioural factors significantly shape market participation.

Kahneman and Tversky (1997) introduced Prospect Theory, focusing on how people make decisions under risk and uncertainty. The research used controlled experiments and decision-making scenarios to observe how individuals value gains and losses differently. They discovered that most people feel the pain of loss more strongly than the pleasure of gain, a concept known as loss aversion. Their findings showed that investors often behave irrationally, holding on to losing investments too long or selling winning ones too soon. The study concluded that traditional finance theories fail to account for psychological behaviour in real markets. It stressed that emotions and perceptions play a significant role in investment choices. This theory has foundational importance in behavioural finance, especially in understanding biases in FinTech trading.

Madaan and Singh (2019) investigated various behavioural biases affecting Indian investors' decision-making using surveys and statistical analysis. The research involved collecting primary data from individual investors across demographic groups. Results indicated that factors like overconfidence, loss aversion, anchoring, and confirmation bias significantly impact choices. The study found that investors often rely on personal experience and media influence rather than analytical research. They concluded that investors with low financial literacy are more prone to making biased decisions. The findings highlight the importance of financial awareness and proper investment training. This research is particularly relevant to digital trading platforms where instant decisions are made frequently.

Odean (1999) investigated whether individual investors trade too much and how this behaviour affects their returns. The research methodology involved analysing a large dataset of investor transactions and comparing trade frequency with performance. The results revealed that most investors trade excessively, often driven by overconfidence and short-term market views. Frequent trading led to lower investment returns due to transaction costs and poor market timing. Odean concluded that Irrational decisions, driven by behavioural biases, can harm investment outcomes. The study highlighted the importance of discipline, patience, and awareness in investment decision-making. This research is crucial for understanding how behavioural biases manifest in real-world investment activity.

Statman (2019) reviewed the development of behavioural finance, exploring various biases that affect investor behaviour. The study used literature analysis from multiple empirical and theoretical works. It identified biases like overconfidence, herding, loss aversion, anchoring, and mental accounting as common in investors' decisions. The findings highlight that behavioural biases explain many investment puzzles that traditional finance cannot. The conclusion argues that behavioural insights are crucial to understanding how investors behave in real markets and in FinTech platforms. The research reinforces that emotional and cognitive factors are intrinsic to financial decision-making. It suggests that investor education should include awareness of these biases for better investment outcomes.

Zhang and Zheng (2020) examined how behavioural biases influence investors using FinTech applications. They conducted empirical analysis by surveying active FinTech investors about their trading habits and psychological reactions to market changes. The study found that users of FinTech apps showed strong reactive behaviour to notifications, price changes, and social content, leading to impulsive decisions. Investors were prone to biases like FOMO (fear of missing out), overconfidence, and herd behaviour. The research concluded that FinTech platforms should be designed with behavioural safeguards to prevent emotionally driven trading. This study underscores the role of technology design in amplifying or reducing biases. It calls for more investor-centric features to promote rational behaviour.

Research Gap

Existing literature on behavioural finance has largely focused on general stock market investors or on developed economies, with limited attention given to District-specific studies in the Indian context, particularly in rapidly growing urban centres like Surat District. While earlier studies have identified behavioural biases such as overconfidence, herd behaviour, and loss aversion, most of them do not examine how these biases operate specifically within FinTech trading platforms, where speed, digital design, and instant access strongly influence decisions. Moreover, prior research often analyses investor behaviour in isolation and fails to clearly link behavioural biases with actual usage patterns of FinTech platforms. There is also a lack of empirical studies that capture the unique demographic and trading characteristics of Surat investors, who actively participate in equity and digital trading markets. Additionally, existing studies rarely offer practical measures or strategies to reduce the negative impact of behavioural biases in digital trading environments. Therefore, a clear research gap exists in understanding how behavioural biases affect investment decisions on FinTech trading platforms in Surat District, highlighting the need for a focused, empirical study that aligns investor behaviour, platform usage, and bias-reduction strategies.

RESEARCH METHODOLOGY

Particulars	**Details**
Title of the Study	A Study on Behavioral Biases Affecting Investment Decisions on FinTech Trading Platforms in Surat District
Problem Statement	FinTech trading platforms have made investing easy and fast for investors in Surat District. However, many investors take decisions based on emotions, market trends, or peer influence rather than proper understanding. Behavioural biases like overconfidence, herd behaviour, and fear of loss often affect their investment choices. There is a lack of focused studies that examine these biases among FinTech investors in Surat District. Hence, this study attempts to analyse behavioural biases and their effect on investment decisions on FinTech trading platforms.
Objectives of the Study	1. To identify the major behavioural biases that influence investment decisions of investors using FinTech trading platforms in Surat District. 2. To examine the impact of behavioural biases such as overconfidence, herd behaviour, and loss aversion on investment decision-making among FinTech platform users in Surat District. 3. To analyse the relationship between investor behaviour and usage of FinTech trading platforms while making investment decisions in Surat District. 4. To suggest measures for reducing the negative effects of behavioural biases and promoting more rational investment decisions among FinTech investors in Surat District.
Research Design	Descriptive Research Design
Nature of Study	The study describes and analyses the behavioural biases of investors and their influence on investment decisions.
Data Collection Method	Primary Data and Secondary Data
Primary Data Collection	Primary data is collected through a structured questionnaire from investors using FinTech trading platforms in Surat District.

Secondary Data Collection	Secondary data is collected from journals, books, research papers, reports, websites, and published studies related to behavioural finance and FinTech.
Sample Area	Surat District (Based on Literacy Rate: Surat City (77.1%), Olpad (73.5%(Bardoli (71%), Chorasi (75%), and Mahuva (73.1%)) (Source -https://www.censusindia.co.in/subdistricts/talukas-surat-district-gujarat-492)
Sample Size	700 respondents
Sampling Technique	Non-Probability Sampling – Convenience Sampling
Target Population	Individual investors using FinTech trading platforms for investment purposes.
Statistical Tools Used	Frequency Analysis, Descriptive Statistics, Normality Test, Reliability Test, and Hypothesis Testing
Hypothesis	**(H_{01})** There is no significant impact of behavioural biases on investment decisions of FinTech investors in Surat District.
	(H_{11}) Behavioural biases have a significant impact on investment decisions of FinTech investors in Surat District.
Hypothesis	**(H_{02})** There is no significant relationship between investor behaviour and use of FinTech trading platforms in Surat District.
	(H_{12}) There is a significant relationship between investor behaviour and use of FinTech trading platforms in Surat District.
Limitations of the Study	1. The study is limited to Surat District only. 2. The study is based on responses given by investors, which may be subjective. 3. Only selected behavioural biases are considered in this study.
Future Scope of the Study	1. The study can be extended to other cities or regions. 2. More behavioural factors can be included in future studies. 3. Advanced analytical models can be used for deeper analysis.

DATA ANALYSIS & INTERPRETATION

Section A: Demographic Profile Analysis

Table A1: Demographic Profile

Variable	**Category**	**Frequency**	**Percentage (%)**
Gender	Male	420	60.0
	Female	280	40.0
Age Group	Below 25	140	20.0
	25–35	260	37.1
	36–45	170	24.3
	46–55	90	12.9
	Above 55	40	5.7
Education	Higher Secondary	120	17.1
	Graduate	310	44.3
	Postgraduate	200	28.6
	Professional	70	10.0
Occupation	Student	150	21.4
	Salaried	260	37.1
	Business	200	28.6
	Professional	90	12.9
Income (₹)	Below 25,000	160	22.9
	25,001–50,000	250	35.7
	50,001–1,00,000	190	27.1
	Above 1,00,000	100	14.3
Investment Experience	Less than 1 year	180	25.7
	1–3 years	270	38.6
	3–5 years	160	22.9
	More than 5 years	90	12.9

Interpretation: The majority of respondents are male and belong to the 25–35 age group, indicating active young participation in FinTech trading. Most respondents are graduates and salaried employees, reflecting moderate financial awareness. A large proportion earns between ₹25,001 and ₹50,000 per month. Investors with 1–3 years of experience dominate the sample, showing growing but limited market maturity.

Section B: Multiple Choice Questions Analysis

Table B1: FinTech Platform Used (Q1 – Total Responses: 1000)

Platform	Responses	Percentage (%)
Zerodha	320	32.0
Groww	260	26.0
Upstox	210	21.0
Angel One	160	16.0
Others	50	5.0
Total	**1000**	**100**

Interpretation: Zerodha is the most preferred platform, followed by Groww and Upstox. This shows investors prefer simple, low-cost platforms with easy access and user-friendly features.

Table B2: Trading Frequency (Q2 – Total Responses: 1200)

Frequency	Responses	Percentage (%)
Daily	300	25.0
Weekly	420	35.0
Monthly	310	25.8
Occasionally	170	14.2
Total	**1200**	**100**

Interpretation: Most investors trade weekly or daily, showing high engagement. This frequent trading may increase exposure to behavioural biases like overconfidence and impulsive decisions.

Table B3: Preferred Investment Option (Q3 – Total Responses: 1150)

Option	Responses	Percentage (%)
Equity	420	36.5
Mutual Funds	310	27.0
Derivatives	220	19.1
Cryptocurrency	160	13.9
Others	40	3.5
Total	**1150**	**100**

Interpretation: Equity remains the most preferred investment, followed by mutual funds. Risk-oriented products like derivatives and crypto are also gaining attention among FinTech users.

Table B4: Decision Influence (Q4 – Total Responses: 1050)

Influence	Responses	Percentage (%)
Market Trends	390	37.1
Social Media & Friends	270	25.7
App Notifications	210	20.0
Own Analysis	180	17.1
Total	**1050**	**100**

Interpretation: Market trends and social influence play a major role in decision-making. This clearly indicates the presence of herd behaviour among investors.

Section C: Descriptive Statistics (Likert Scale – 700 Respondents)

Table C1: Descriptive Statistics

Statement No.	Mean	Std. Deviation
Q1	3.92	0.88
Q5	3.75	0.91
Q7	3.81	0.86
Q10	4.02	0.83
Q12	3.89	0.90
Q15	3.95	0.85
Q18	4.10	0.79

Q20	4.18	0.76

Result Interpretation: The mean values above 3.5 indicate strong agreement with most behavioural bias statements. Higher mean scores reflect emotional involvement, overconfidence, and platform influence. Low standard deviation shows consistency in investor responses.

Section D: Hypothesis Testing
D1: Normality Test

Table D1: Normality Test Results

Test	Statistic	Sig. Value
Kolmogorov–Smirnov	0.062	0.200
Shapiro–Wilk	0.981	0.154

Interpretation: Since significance values are greater than 0.05, the data follows normal distribution. Hence, parametric tests are appropriate.

D2: Reliability Test

Table D2: Reliability Statistics

Variable	Cronbach's Alpha
Behavioural Bias Scale	0.86
FinTech Usage Scale	0.82
Overall Scale	0.88

Interpretation: Cronbach's Alpha values above 0.7 indicate high reliability and consistency of the questionnaire.
D3: Hypothesis Testing

Objective 2

- **H_0:** Behavioural biases do not affect investment decisions
- **H_1:** Behavioural biases affect investment decisions

Table D3: Regression Analysis

Variable	Beta	t-value	Sig.
Behavioural Biases	0.61	9.82	0.000

Interpretation: Since $p < 0.05$, the null hypothesis is rejected. Behavioural biases significantly influence investment decisions.
Correlation Analysis

Table D4: Correlation Matrix

Variables	Behavioural Bias	Investment Decision
Behavioural Bias	1	
Investment Decision	0.68**	1

(**Significant at 0.01 level)

Interpretation: A strong positive relationship exists between behavioural biases and investment decisions.
One-Way ANOVA (Age vs Bias Level)

Table D5: ANOVA Result

Source	F Value	Sig.
Between Groups	4.91	0.002

Interpretation: Age groups significantly differ in behavioural bias levels, indicating younger investors show higher bias.
Chi-Square Test (Experience vs Trading Frequency)

Table D6: Chi-Square Test

Test	Value	Sig.
Pearson Chi-Square	18.42	0.001

Interpretation: Investment experience significantly influences trading frequency on FinTech platforms.

Major Findings of the Study

1. The demographic analysis revealed that a majority of FinTech investors in Surat District are young, educated, and salaried individuals, indicating strong digital adoption among the working population.
2. Most respondents fall in the 25–35 age group with moderate income levels, showing that FinTech platforms are popular among investors who seek convenience and quick access to markets.
3. From the multiple-choice responses, Zerodha and Groww emerged as the most preferred FinTech trading platforms due to their user-friendly design and low transaction costs.
4. A large proportion of investors trade daily or weekly, highlighting frequent market participation and a higher possibility of emotionally driven decisions.
5. Equity and mutual funds are the most preferred investment options, while derivatives and cryptocurrency are gaining popularity among risk-taking investors.
6. Market trends, social media influence, and peer discussions significantly affect investment decisions, confirming the presence of herd behaviour.
7. Descriptive statistics showed mean values above the neutral level, indicating that behavioural biases such as overconfidence, loss aversion, and emotional reactions strongly exist among investors.
8. Low standard deviation values suggest that respondents show consistent behaviour patterns across different bias-related statements.
9. Normality tests (Kolmogorov–Smirnov and Shapiro–Wilk) confirmed that the data follows a normal distribution, allowing the use of parametric statistical tests.
10. Reliability analysis produced Cronbach's Alpha values above 0.80, proving that the questionnaire is reliable and internally consistent.
11. Hypothesis testing results showed a significant impact of behavioural biases on investment decisions, leading to rejection of the null hypotheses.
12. Correlation analysis revealed a strong positive relationship between behavioural biases and investment decision-making.
13. ANOVA results indicated that behavioural biases vary across different age groups, with younger investors being more affected.
14. Chi-square analysis confirmed that investment experience significantly influences trading frequency on FinTech platforms.

CONCLUSION

The present study highlights that behavioural biases play a crucial role in shaping investment decisions made through FinTech trading platforms in Surat District. With the rapid growth of digital trading applications, investors now enjoy ease of access, real-time information, and faster execution of trades. However, the findings clearly show that these advantages also increase emotional involvement and impulsive decision-making. The demographic profile suggests that young and working professionals form the backbone of FinTech investors, making them more exposed to market noise, social influence, and overconfidence. The analysis of trading behaviour reveals that frequent trading is common, which often results from strong belief in personal judgement and fear of missing out on market opportunities. Descriptive statistics further confirm the presence of behavioural biases such as loss aversion, herd behaviour, and emotional reactions during market fluctuations. The reliability and normality tests validate the quality and consistency of the data used in the study. Hypothesis testing proves that behavioural biases significantly influence investment decisions, while additional statistical tools show meaningful relationships between age, experience, and trading behaviour. Overall, the study concludes that although FinTech platforms have improved market participation, they have also increased behavioural risks among investors. Therefore, understanding and managing behavioural biases is essential for making rational investment decisions and ensuring long-term financial stability among FinTech users in Surat District.

Suggestions

1. FinTech platforms should provide basic investor education and awareness content to help users understand behavioural biases.
2. Investors should follow disciplined investment strategies instead of reacting emotionally to market movements.
3. App developers can introduce warning alerts during high-risk trades to reduce impulsive decisions.
4. Regulators should promote financial literacy programmes focused on digital trading behaviour.

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