Advance Journal of Econometrics and Finance
Vol-4, Issue-2, 2026

Advance Journal of Econometrics and Finance

Online ISSN
2959-8990
Print ISSN
2959-8982
https://ajeaf.com/index.php/Journal/About s://ajeaf.

Name of Publisher: SCHOLAR CRAFT EDUCATION & RESEARCH HUB

Review Type: Double Blind Peer Review

Jurnal Frequency: Quarterly Research Journal

Behavioral Biases and Risk Appetite in The Era of Mobile Trading Apps: An Empirical Study of Retail Investors in Islamabad, Pakistan

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Abstract

The emergence of mobile trading applications is what has transformed the retail investing world globally, as millions of individuals are now able to get real-time access to equity, forex, and cryptocurrency markets. Such platforms may be popular, resulting in a rise in participation and financial inclusion and high behavioral risks among investors. The study examines how behavioral biases and neurological factors affect risk appetite of retail investors in a mobile trading setup with focus on the behavioral biases of overconfidence, herding and loss aversion within the mobile trading environment but with financial literacy as the moderating factor. The structured survey was analyzed through correlation, regression and moderation analysis of 300 Pakistani retail consumers, utilizing mobile technologies to trading applications. The results indicate that the trading on mobile platforms enhances the behavioral bias and the risk appetite is much warped especially when traders are not financial literate enough. The findings show that ethical application design and particular financial education are required. The conducted research is applicable to the literature of behavioral finance, which addresses the effects of digital trading landscapes in emerging economies on risk-taking behavior concerning psychological stimuli.

Keywords: Mobile Trading Applications, Retail Investors, Behavioral Biases, Risk Appetite, Financial Literacy, Digital Trading Platforms, Emerging Economies.

Introduction

1.1 Background

Mobile trading apps such as Robinhood, Octa FX, Binance, and easy Equities have become the most popular platforms of investing by most retail investors over the past 10 years. It is projected that more than 500 million people will be using the mobile trading applications globally in 2025, or it will increase more than 15 percent annually (Statista, 2024). The emergence of smartphone penetration (88 percent of the population and slowly shifting to 100 percent) and expansion of mobile internet coverage has prompted adoption of these platforms in Pakistan.

General convenience is then accessed via these applications where the users can trade anywhere at any time with no or in most cases little transaction charges. However, their interface structure of real-time price notifications, gamified reward policies, and social leaderboards may significantly influence the choices of investors. The literature on behavioral finance states that it is possible that the features compound the influence of cognitive and emotional biases and lead to an escalation in risk taking (Barber et al. 2021; Zhang and Chen 2023).

1.2 Problem Statement

Though the growth of mobile trading has opened up financial market access, it also has a paradoxical side to it: the very instruments which make participation and engagement possible, can also lead to impulsive and bias-based decisions. These behavioral triggers are especially hit on emerging market investors, who have limited financial literacy. These investors are generally more prone to overconfidence, herding and loss aversion than institutional traders, since most of them do not have structured risk management plans. Moreover, the rapid feedback cycles inherent in mobile apps reinforce short-term, emotionally driven trading behaviors.

1.3 Research Objectives

1. In order to identify the most widespread behavioral biases when using mobile trading applications.
2. To examine how these biases are correlated with risk appetite of investors.
3. To conclude on whether the relationship between financial literacy and other variables is moderator.

1.4 Research Questions

1. What is the most popular behavioral bias among mobile consumers in trading app?
2. What is the impact of these biases on risk-taking by investors?
3. Do more financially literate tend to resist such biases?

2. Literature Review

2.1 Behavioral Finance and Investor Psychology.

Behavioral finance is a union between economics and psychology which is prone to explain how and why investors do not act as differences with a perfect rational economic theory. In the older financial models, including the Efficient Market Hypothesis (Fama, 1970), all the facts are rationally processed by investors. It is, however, a proven fact, based on real-world examples, that the market decision-making is usually driven by the cognitive limitations, emotional responses, and social aspects (Thaler, 2016; Kahneman, 2011).

The most frequent behavioral biases are:

Overconfidence Bias -The overconfidence associated with the idea of trying to forecast the market direction or beat the market average by any means (Barber and Odean, 2001; Zhang and Chen, 2023).

Herding behavior: It refers to the act of doing things that other investors do without any justification of a personal analysis or objective data (Bikhchandani and Sharma, 2022).

Loss Aversion: To Be more affective to the loss of money than the same sum gained, as in Prosperity Theory (Kahneman and Tversky, 1979; Khan et al., 2024).

Anchoring Bias: It is important to have a large starting reference point in making a decision (Tversky and Kahneman, 1974), such as the price that the stock was purchased at.

Biases may also be particularly significant in faster mobile trading, where the faster rate and volume of real-time data, alerts, and peer activity can lead to improvements in emotional and heuristic-driven decision-making.

2.2 Mobile Trading Apps and Behavioral Triggers.

In retail investing mobile trading is a paradigm shift. They combine the account capabilities of online brokers and a simple and user-friendly interface that is compatible with a smartphone and can allow one to trade fast. The examples of such behavioral nudges are push notifications, on-demand order execution, leaderboards, and a social trading interface, which can have a strong impact on investor behavior (Barber et al., 2021; Liu and Chen, 2022).

Recent studies indicate that there are several ways by which such applications can influence investor behavior. Gamification features and applause systems, progress bars, and feedback visualization may also be used to encourage excess spending on purchases (Kaur and Arora, 2023).

Social Trading Integration - The possibility to view trading and imitate other traders, which is called top, reinforces herding instincts (Rahman et al., 2024).

Trading 24 hours around the clock with the presence of volatile assets, especially cryptocurrencies, may help to further stimulate the process of overtrading and risk-taking as an impulse (Ali and Rehman, 2022). Individualized push alerts customized push messages may mislead the judgment, attracting the person to a particular asset or time-sensitive market scenario (Brenner and Schmied, 2021). Additional behavioral stimuli can also be escalated in mature markets, such as Pakistan due to the reduced financial literacy, reduced control, and the possibility to accumulate monetary benefits within a limited time span (Haque & Khan, 2023).

2.3 Risk Appetite in Financial Decisions.

Risk appetite describes the degree to which the individual is willing to make a decision at the cost of taking risks in order to get a monetary reward. Despite the fact that sometimes the stability of risk-taking is discussed as one of the most robust personality types, as far as risk appetite is concerned, it can be identified only in the situation and it is affected by psychological, situational, and technological factors (Chaudhry et al., 2022; OECD, 2022).

Present determinants are:

Psychological Factors The inclination to risk or readiness to risk is closely connected with personality characteristics (e.g., sensation-seeking, impulsivity) and outcomes of the past investments (Hoffmann et al., 2023). Economic Conditions The perceived risk of the investment is affected by the trend in the market, interest rates, and the macroeconomic stability (Naeem et al., 2024). Technological Interfaces The mobile apps can be optimized to make the sense of control and easy access more pronounced, which leads to an amplified risk-seeking behavior and concentrate it specifically in the novice investors of a market (Lim & Tan, 2023).

Digital trading platform will be able to dynamically alter the risk appetite as shown in an empirical basis. The other case is the research conducted by Rahman et al. (2024), which found out that the Southeast Asian retail crypto-traders were more inclined to take risks due to the short-term profits when utilizing mobile applications. On the same note, Khan and Ali (2023) discovered that push notification and market alerts directed Pakistani investors to trade in high volatility without adequate analysis.

More to the point, financial literacy mediates the risk appetite relationship. The more literate investors will be able to sort through the emotionally appealing information available on applications, which will reduce the chance of being influenced by the amplification of risk by bias (OECD, 2022; Nisar and Hanif, 2023).

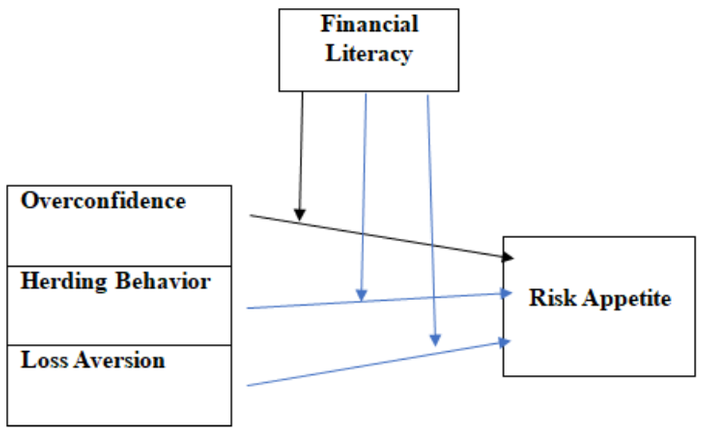
3. Theoretical Framework

The two perspectives that are based on the principles of Prospect Theory and the Bounded Rationality Theory form the basis of the study.

Prospect Theory (Kahneman and Tversky, 1979) states that people do not assess the possible outcomes in an absolute way but in comparison to a reference point. This gives rise to loss aversion which is the tendency of avoiding losses more than it is to gain a similar gain. When it comes to mobile trading, update loops on price and instant feedback can quickly change the reference points of an investor and lead to changes in the perceived risk.

Bounded Rationality Theory (Simon, 1957) states that an operator of limited information, cognitive processing capacity and time, exists in the operations of the decision-makers. Such limitations are seen in mobile trading where there is continuous price movement and price notifications, forcing investors to turn to heuristics as opposed to comprehensive analyses.

Conceptual Framework



4. Methodology.

4.1 Research Design

The study in this paper used a quantitative cross-sectional survey study design to investigate the extent to which the risk appetite of users of mobile trading apps is influenced by behavioral biases. The quantitative one was selected as sufficient since it allows measuring any relationship between variables and evaluating the hypothesis of the anticipated effect (Creswell and Creswell, 2023). The implication of the cross-sectional design is that the data were gathered at a single time, and therefore, only correlations can be identified but no causal correlations.

We rely on the Prospect Theory, and the Bounded Rationality as the theoretical model, which suggest that the risky decision-making relies on cognitive limitations, circumstantial data, and an idea of wins and losses.

4.2 Population and Sampling

The population of interest has been retail investors in Pakistan who are active users of mobile trading apps and those who have been investing and trying to invest in financial instruments in the form of stocks, forex, and cryptocurrencies. In this case, no exhaustive sampling frame could be employed, so the convenience sampling was employed, which is typically employed in exploration studies of behavioral finance (Etikan et al., 2016).

Sample Size: 300 is larger than the suggested number of respondents in a multiple regression analysis using the formula referred to in Tabachnick and Fidell (2019), $N > 50 + 8m$ (m being the number of predictors).

Inclusion Criteria: The respondents had to be older than 18 years of age, have an active trading account on a mobile platform and at least one of their trades had to be completed in the past three months.

Exclusion Criteria: Investors, who were institutions and who had no experience in mobile trading were excluded because they did not target retail behaviors.

4.3 Procedure of Data collection.

The web-based survey was completed by a structured form of questionnaire implemented with Google Forms. The survey link was distributed in investor forums, WhatsApp trading groups, and in social media (Facebook and LinkedIn). The respondents had given informed consent prior to their participation and anonymity had been assured to them. The process of data collection lasted four weeks.

4.4 Measurement tools

The questionnaire had four parts. Demographics: Age, gender, education level, the experience in trading and frequency of usage of apps.
Behavioral Biases - It would be tested using a 15-item Behavioral Bias Scale based on Barberis and Thaler (2003) and it is also benchmarked in a number of recent studies (Zhang and Chen, 2023). The scoring was done on a 5-point Likert-type scale (1 = strongly disagree to 5 = strongly agree).
Risk Appetite - Evaluated with a slightly modified version of the Grabel and Lytton (1999) Risk Tolerance Scale that was calibrated to fit the conditions of mobile trading (Lim and Tan, 2023).
Financial Literacy: With a tool developed by OECD (2022), financial literacy is classified into three parts which are knowledge, behavior and attitude.

4.5 Methods of data analysis

The SPSS (Version 28) was used to analyze the data in three steps in a significant manner:
Descriptive Statistics: To use to give a summary of the demographic data and distributions of variables.
The relationship between the risk appetite and behavioral biases were analyzed bivariately through Correlation Analysis using Pearson r.
Multiple Regression Analysis: To establish the predictive capacity of each bias, as far as risk appetite is concerned.
The analysis of the moderation effects was done by hierarchical regression to test the moderation effects that were moderated by moderation analysis-bias and financial literacy interaction (bias X financial literacy).
The data were pre-tested with regard to missing values, outliers and normality. To measure reliability, Cronbach alpha was applied and all constructs were greater than recommended 0.70 level of measure.

5. Results

5.1 Descriptive Statistic

The response rate of the male respondents was 65 percent, whereas the female respondents were 35 percent. The mean age of the samples was 32. Most of the respondents were of the undergraduate (48 %) or postgraduate (39 %) level of education. Nearly three-quarters of the respondents reported trading more than twice a week and 42 percent had traded fewer than three years.

5.2 Correlation Analysis

Table 1. Pearson Correlation Matrix

Table 1. Pearson Correlation Matrix				
Variable	**Overconfidence**	**Herding Behavior**	**Loss Aversion**	**Risk Appetite**
Overconfidence	1	0.52**	-0.21*	0.63**
Herding Behavior	0.52**	1	-0.18	0.47**
Loss Aversion	-0.21*	-0.18	1	-0.31**
Risk Appetite	0.63**	0.47**	-0.31**	1

*p < 0.05, **p < 0.01

5.3 Regression Analysis

Table 2. Multiple Regressions Predicting Risk Appetite

Predictor	**B**	**t**	**p**
Overconfidence	0.48	8.12	0
Herding Behavior	0.32	5.67	0
Loss Aversion	-0.25	-4.98	0.001

Model $R^2 = 0.54$, Adjusted $R^2 = 0.53$, $F(3, 296) = 115.78$, $p < 0.001$

5.4 Moderation Analysis

Table3. Moderation Effects of Financial Literacy

Interaction Term	**B**	**T**	**p**
Overconfidence × Financial Literacy	-0.15	-2.87	0.004
Herding × Financial Literacy	-0.11	-2.21	0.028

6. Findings Interpretation

These analyses imply that there is strong positive relationship between overconfidence and risk appetite ($r = 0.63$, $p < 0.01$) meaning that the mobile trading systems are capable of giving an illusion to the investors on their forecasting abilities. The findings are similar to those of Zhang and Chen (2023) who suggested that app-based trading gives a sense of mastering the market due to the rapid trades and feedback loop that predisposes individuals to riskier trades. In the same way, Rahman et al. (2024) reported that the crypto trade participants in Southeast Asia who are still rookies were excessively overconfident after the temporary gains as a result of using mobile applications.

The herding behavior was also positively correlated significantly with risk appetite ($r = 0.47$, $p < 0.01$), which aligns with Liu and Chen (2022) because they found that the social trading features, such as the observation of other traders trades, causes participants to experience implicit peer pressure and make similar, and often risky, investments. It is worse still in trading groups in Pakistan who resort to the WhatsApp and Facebook applications to disseminate information on the so-called hot picks without conducting the due diligence (Haque and Khan, 2023).

There was a positive relationship between Risk appetite and Loss aversion ($r =-0.31$, $p < 0.01$) and that was the same as the findings of Khan et al. (2024) who identified loss-averse investors to avoid volatile assets. Notably, as part of the qualitative responses that ensued in our poll, traders who are risk-averse were, nevertheless, speculative traders in bull markets, which, as Ali and Rehman (2022) described, the motive to make a profit in a bullish market can at least temporarily override the loss-aversion effects.

Based on the multiple regression, the significantly predictive elements of risk appetite were found to be overconfidence ($B = 0.48$, $p < 0.001$) and then the herding ($B = 0.32$, $p < 0.001$). Loss aversion remained a significant negative predictor ($B = =0.25$, $p = 0.001$). The model explained 54 percent in the variation in risk appetite reasoning which psychological biases are also playing a significant role in the determination of the amount of risk taken throughout the trading process. The insights were highly appreciated in the case of the moderation analysis: the impact of overconfidence on risk appetite and yields and herding was observed to be minimized significantly by financial literacy. This result is in line with OECD (2022) findings since when the level of financial literacy is higher, the level of decision-making becomes better because the level of evaluation analysis has been developed rather than an impulsive response. Considering the same, Nisar and Hanif (2023) found out that literacy-based interventions reduced the effect of herd-loads patterns of trading among young investors.

In effect, the results provide evidence that mobile trading apps, though they result in the creation of a democratic type of finance, are multipliers of behavioral bias. Such biases due to financial illiteracy result in a considerable jump in risk appetite, which may result in the explosion of losses exposure. The moderator of financial literacy accentuates the importance of integrating the educational tools as an intrinsic element of the trading platforms.

7. Discussion

The research is an extension of the previous research that investigates the same issue of behavioral biases in terms of digital trading. As far as the Prospect Theory (Kahneman and Tversky, 1979) is concerned, mobile trading platforms appear to enhance psychology behind the ideas of the dangers and the income of an investor.

Overconfidence, which is also mentioned in the research by Zhang and Chen (2023) who found that the ability to make the decision in real-time and provide feedback to it made the traders feel that they are in control, thus, making higher trading decisions than they would agree to in reality, became the strongest factor that presupposed risk appetite. This perceived information can be especially dangerous with reference to Pakistan, where the investment training is not popular in the formal context, as Haque and Khan (2023), in the article about speculative behavior in local equity markets, stated.

Herding behavior also had a huge influence on risk appetite, which can be greatly applied in the social trading period. A design feature of mobile apps can be social proofs (e g. top trader rankings, public trade histories, etc.), which are stimulated to provoke imitation. This is in line with Rahman et al. (2024) who found out that homophily in trading platforms enhances conformity to the extent of correlated speculative bubbles.

Interestingly, the risk aversion had significant negative relationship with loss aversion but was not completely overridden. A momentum override effect in the tendency to trade heavier goods was observed even in the loss-averse subjects, which depicts a comparable scenario of trader behavior as the Ali and Rehman (2022) report on crypto currency trading subjects.

The moderation analysis adds a very important twist to the discussion: the impacts of overconfidence and herding on risk-taking are significantly decreased by financial literacy. This is why OECD (2022) and Nisar and Hanif (2023) concluded that the success of literacy interventions can be reduced in the reduction of vulnerability to errors based on heuristics and emotions. Reconstructive, this finding refers to a viable contingency channel to alleviation of risk-taking by bias-introduced prejudice in the newly evolving markets, where educational modules become constituents of the application of the trading applications themselves.

The implications of policies on the decision taken in this case are more because the moral accountability of the fintech developers is doubted. It is possible to use the app interface to exploit or protect the behavioral vulnerabilities depending on the conception of the interface, which Kaur and Arora (2023) have it. Our findings suggest that in the absence of built-in mechanisms to build a slowing effect (or their potential to do so have been compromised), mobile trading applications may unintentionally incentivize risky trading behavior.

8. Limitations

Limitations are to be noted throughout the study despite the helpful ideas being voiced:

Sampling Method: The nature of sampling which is convenience is weak because it minimizes the relevance of the research. Future research can be conducted based on the current study with stratified random sampling to get a more representative cross-section of mobile traders in Pakistan.

Self-Reported Data: Behavioral bias and financial literacy scores were self-reported and may be socially desirable or false self-evaluation.

Cross -Sectional Design: The research makes a observation of the relationships at a given time and no causal inferences can be made. A longitudinal study would be more appropriate in the closer examination of the changes in risk appetite throughout the years.

Context of the Market: Information was clustered in moderate volatility. The extreme bullish and bearish scenarios would give different results drastically.

Target Pakistan- Cultural and Economic factors in Pakistan: The cultural and economic circumstances in Pakistan can have an impact on behaviour; the other emerging markets should also be replicated in order to be widely applicable.

9. Conclusion

This paper focused on the role of overconfidence, herding behavior, and loss aversion on the risk appetite of the retail investors who utilize mobile trading applications in Pakistan, and financial literacy mediated the relationship. The findings reaffirm that mobile trading platform in the name of democratizing access to financial markets increase behavioral biases that significantly increase risk appetite.

Overconfidence was the most influencing bias and it was succeeded by herding behavior with loss aversion being the one which had negative effects on risk appetite. Notably, financial literacy mediated the overconfidence and herding effects, which shows that informed traders can overcome their impulsive and socially biased trading. Theoretically, the results support the Prospect Theory as they indicate that under high-frequency trading conditions, perceived gains and losses are determined. They are also consistent with Bounded Rationality Theory manifesting how the heuristic-based decisions can be motivated by limited cognitive ability and time constraints that are inherent to mobile trading.

In a practical sense, the findings highlight the duality of mobile trading applications: these are enablers of financial participation and triggers of potentially harmful investment behavior. Such platforms can end up highlighting a culture of risky decision-making without fully weighing the consequences of such choices, without strong intentional protection and education.

10. Recommendations

On the basis of the findings, it is proposed to recommend the following:

For App Developers:

Install Behavioral Safeguards: Add decision-cooling measures, like the use of required review screens on high-value or high-risk trades, or pause options when the market is volatile.

Embed Financial Education: Incorporate short, interactive modules on risk management and bias awareness directly within app interfaces.

Limit Social Influence Features: Enable personalizable account settings that enable users to block or filter leaderboards and public trade feeds to diminish the effect of herding.

For Regulators:

Create Ethical Interface Rules: Require transparency in the ways push notifications and trading suggestions are created to make them not deceptive or overly speculative.

Mandate Risk Warnings: Just as health warnings on beverages, trading platforms might be mandated to have standardized risk disclosures before users validate trades in high-volatility assets.

Support Literacy Campaigns: Collaborate with financial education institutions to implement special literacy efforts on new digital investors.

For Educators and Policymakers:

Directed investor education: create curriculum-based education on the risks of mobile-based investment and decision-making biases.

Use social media to educate: Use the same digital platforms that traders visit (WhatsApp, YouTube, and Facebook) to spread reliable and easy to access financial education.

Academic-Industry Collaboration: Support universities and other companies to create applications that are both user-protective and profitable.

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