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# GAMIFICATION OF STOCK TRADING AND ITS IMPACT ON RETAIL INVESTORS IN INDIA

**Adwaith Gopan** Research Scholar, Department of Economics, Govt College Attingal

**Dr Binu Kumar B. J.** Assistant Professor and Research Guide, Department of Economics, MG College Thiruvananthapuram.

**ABSTRACT** **Summary:** The influence of behavioural biases on decision-making has been studied extensively, but relatively less literature is available on the role of gamification in decision-making. The study focuses on gamified trading platforms and how they use behavioural biases to influence retail investors. There are two objectives: To identify the behavioural biases that affect the investor and their extent of influence on the investor. Five behavioural biases were selected: Anchoring, herding, availability heuristics, loss aversion, and overconfidence bias against the dependent variable volume of trade. **Methodology:** The samples are collected mainly from Kerala, a state of India. Seventy-one investors were selected using the snowball sampling method. The regression analysis was used to find the relationship between the volume of trade and cognitive biases. **Findings:** The regression analysis finds a significant association between cognitive biases and the volume of trade of the investors. Anchoring, loss aversion and herding behaviour differ significantly between male and female investors. The beta coefficient of availability is 0.727, loss aversion is 0.676, anchoring is 0.646, herding is 0.821, and overconfidence bias is 0.958. The model has a high R2 value of 0.64 and an Adjusted R2 value of 0.613.

**KEYWORDS :** Cognitive bias, anchoring, availability heuristics, herding, loss aversion, overconfidence bias, volume of trade..

## INTRODUCTION

Gamification is a relatively new term that has been used frequently in recent times. Unknowingly, we all have been a part of this so-called "process." Gamification is the application of game design elements in a non-game context (Deterding, S. et.al., 2011). Our education system is an example of gamification in real life, where students progress from each level from easy to hard (Dichev, C. et.al., 2017). The world of the stock market is often considered a complex concept for the common man, thus preventing them from investing in it. With the advent of the internet, people have become more interested in investing in the stock market (S. Chaudhary et al., 2021). The applications like Groww and Upstox have created a platform for aspiring investors. These applications use the gamification technique to attract new users and keep their existing ones (Bayuk, J. 2019).

The era of the internet came relatively late in India compared to other countries. The Internet reached the masses of India in 2016 when internet providers decided to reduce the price of 4G data packs (R. Holla, 2016). Though late, the internet took India by storm, the e-commerce market grew from \$5.3 billion in 2014 to \$17.52 billion in 2018. The convenience brought upon by the internet has extended to the world of financial markets and mobile applications for investing targeting retail investors have arrived in India (Vijai, C., 2019). The experiment was successful in India, as the number of users on these platforms spiked at an unprecedented rate post-2019. This can be attributed to the COVID-19 pandemic, where people were desperate to seek new sources of income due to the uncertainties caused in the labour market by the pandemic (Talwar, M. et.al., 2021). Up until 2018, the government of India did not impose taxes on short-term capital gains (STCG) this has resulted in a surge in retail investors in the Indian stock market forcing the government to impose a 15% tax on STCG in 2018. Despite the imposition of tax on the STCG, retail investing in India flourished post-COVID-19 pandemic. The rise of crypto and non-fungible tokens (NFT) has also attracted the youth demographic to world stock marketing (Taherdoost, H. 2023). The applications that support crypto transactions like CoinDCX use the principles of gamification to gain potential users.

Retail investors, especially beginners, may not make an informed decision, as they are mostly unaware of the fundamentals of trading and might have started training due to the bandwagon effect (S. Wei Xiang et al., 2022). Therefore, they are more susceptible to behavioural biases, and gamified stock trading platforms attempt to utilize these biases to keep their users to continue investing (P. Rajagopalan & S. Guruswamy, 2015). The present paper aims to understand the basic gamification principles how susceptible retail investors are to behavioural biases and the extent of influence of gamified trading platforms.

### Principles Of Gamification

The principles of gamification lay down the foundation for designing a stock trading application. Stock trading applications use these principles to optimize their interaction with the users.

1. **Personalized Experience:** The applications design their interface to the preference of their user; thus, the user feels more comfortable using the application. This will also enable the applications to know the interests of the user and customize advertisements for them. (Francisco, C. M. et.al., 2013)
2. **Continuous Engagement:** The applications aim to maximize user engagement through services that establish and ensure constant engagement from the part of the user (Sironi, 2016).
3. **Encouraging Heuristic Tendencies:** Investing in the stock market requires careful and deliberate decision-making, which would often overwhelm a retail investor. The gamification process would reduce the complex cognitive effort required and simplify it for the user. This will often lead to cognitive biases like availability heuristics (Chaudhary &Kulkarni, 2021)
4. **Optimizing The User's Strategy To Achieve Their Goals:** The applications designed as games treat their users as gamers instead of investors. The apps would provide advice and strategies for the user which would result in achieving their goals. (Sironi 2016)
5. **Rewards And Benefits:** One of the common strategies employed by the applications is rewarding the user for their success. These rewards might be redeemable coins and coupons that provide discounts or other benefits (Francisco, C.M et al., 2013).

### Retail Investors And Their Behavior

According to SEBI, a retail investor is an individual who does not hold or buy stocks above two lakhs. Retail investors, though many, do not have a significant share in the market compared to other participants in the financial market. Contrary to the efficient market hypothesis, investors, especially retail investors, are not rational, and assuming they are rational while making decisions deviates the theory further from reality (Talwar, 2020). Retail investors often make decisions instinctually, believing they made an informed decision. This overconfidence in their ability leads to the underperformance of their stock (Chaudhary & Kulkarni, 2021).

The impressionable behaviour of retail investors became apparent in the non-fungible token (NFT) transactions. Institutional investors often avoid NFTs due to their lack of intrinsic value/utility. These tokens are released by internet influencers targeting their core audience, and at times these end up as pump-and-dump schemes, scamming the investors. NFTs became popular during the early phase of the COVID-19 pandemic, with almost 80% of the NFT transactions being done by retail investors. A similar pattern can be observed in most crypto transactions, where the retail investors solely remain on the losing side of the game. The crypto and NFT applications present their platform as a game where the investors become gamers, and each advancement is rewarded (Parizi and Dehghantanha, 2018). This creates competitiveness among the investors and results in them making irrational decisions and losing money.

Retail investors prefer less risky, high-yield assets over a long period (Kumari, 2017). They are sensitive to sensational news and frequently buy or sell assets on a whim. The investors are heavily subjected to cognitive biases like heuristics and anchoring. Heuristics is the mental simplification of a complex concept, that can lead to misinterpretation and anchoring refers to relying heavily on the first piece of information that is received by an individual. These biases often cloud the judgements of the investor making them overconfident (Vijaya, 2016). The financial literacy of the investor plays an important role in their investment decisions, especially in risky investments. Investors with a higher level of literacy would be able to identify the risky instruments with ease and respond accordingly (Prasad et al. 2018).

## Literature Review

Herding is a relatively new concept in behavioural finance. Herding behaviour is the tendency of individuals to follow or imitate popular choices over their own (M. Baddeley, 2010). It is a common phenomenon in the stock markets among retail investors. A strong market trend favouring a stock will cloud an individual's judgement and make them overlook their analysis in favour of market consensus (Satish & Padmasree, 2018). The recent incidents of GameStop, cryptocurrencies and NFTs are examples of herding behaviour, where investors (predominantly retailers) have invested heavily in these stocks due to their popularity in social media. These stocks' prices sunk sharply a few days later, incurring losses for most of its investors (K. Kim et al., 2022) (Yousuf and Yarovaya, 2022)

Availability Heuristics is a commonly observed phenomenon among human beings. The human mind often relies on immediate examples while analyzing an issue to make decisions in the future. For example, a person is likely to take a lottery if one of his friends or a relative recently won a lottery. There is only a 0.00001% chance of him winning that lottery, but he overestimates the chances of winning it, due to his recent experience (Kahneman & Tversky, 1973). This phenomenon is observed in stock market trading, where investors purchase and sell stocks based on recent trends since they are easy to recall and retrieve (R. Linciano, 2010). The trading applications incorporate the availability heuristic bias in their app design by enabling the users to share their portfolio with others, and their algorithm promotes stocks that are popular among the same demographics of the user, thereby encouraging deliberate trading (Chaudhary, S. & Kulkarni, C. 2021). The apps also tune down the various complex information about the stock in comprehensible manner, which would initiate an easier decision-making process (Ljungkvist, H. et. al. 2022).

Anchoring is another type of behavioural bias observed among individuals. Human beings often make quick decisions or estimations based on the first- piece of information they receive (Tversky& Kahneman, 1974). Investors often judge the viability of a stock based on its previous price point (anchor) and form decisions on whether to buy or sell the stock concerning the anchor, failing to incorporate new information (Tai-Yuen H. et al., 2021). The failure to include information would lead the investor to make incorrect decisions (Hammond, J.H et al., 2006). There are instances of anchoring that can be observed from these platforms, where the apps provide news and analytics of the stocks preferred by the investor (Dickard, M. 2020).

For some individuals' the utility for gains and losses is different, even when the probability of win to loss is 50:50. They will weigh the probable utility lost higher than the utility gained (Kahneman & Tversky, 1979). This is known as loss aversion. Retail investors narrowly define their gains and losses, skewing their risk evaluation this will prompt them to overvalue their losses, preventing them from investing (Barberis, N. and Huang, M., 2001). Despite the belief that loss aversion leads to a fall in investors' confidence and a subsequent fall in app usage (Tomé et al., 2020), there is evidence for the contrary. The apps provide benefits for the users who maintain their streak, like discounts and badges (Georgiou, M. 2022). The apps using game-like presentations would make things seem like they are actual achievements, and convince the user that to reap their benefits would require consistent use (Yu-kai Chou, 2015).

Overconfidence bias occurs when an individual is too confident about their intuitions and refuses to consider the available information (Tversky and Kahneman, 1974). Investors who have had past successes or possess more knowledge/a higher degree of education about the stock markets tend to be overconfident in their abilities (Kumar, J. & Prince, N, 2022). Often this overconfidence will lead to misinterpretation of information and opportunities (Scott, J., et al. 2003). The trading platforms oversimplify the complex nature of the stock market to the investors through their platforms, this positively reinforces their ability to trade making them overconfident in their ability (Cozby, M. 2023).

## Research Gap

After conducting an extensive literature review, the research gap has been identified that the present study attempts to address:

- There are studies based on cognitive biases and investor decision-making, and most of them derived the dependent variable using the Likert scale analysis. The study uses the trade volume as the dependent variable, where the respondent is asked the number of transactions they made in the past three months.
- In India, gamified trading platforms grew in popularity after the COVID-19 pandemic, but few studies have been conducted post-pandemic that focus on investor behaviour analysis.
- The current study is conducted in the Indian state of Kerala. Kerala has the highest HDI among all the Indian states, but stock market trading has not been popular until recently. Therefore, no study explicitly focused on investors in Kerala.

## Objectives Of The Study

- To evaluate the extent of influence of behavioural biases used by FinTech apps on the decision-making of retail investors in India.

## Hypothesis Of The Study

1. $H_0$: There is no significant relationship between cognitive biases and the volume of trade by the investors.

## Methodology Of The Study

### Data Collection

The primary data is collected through the questionnaire method, where the researchers used Google Forms to collect the data from investors. The samples were collected using the snowball sampling method, and most of the respondents were from Kerala, a southern state of India. Snowball sampling is a non-random sampling technique where existing subjects recruit further samples (B. Arathy et al. 2015). It is used when the samples are difficult to locate due to their distinctive characteristics (G.R. Sadler et al. 2010). The study is conducted using the e-questionnaire method, and it is hard to find retail investors who use stock trading apps; thus, the snowball sampling method is the appropriate method for the study (P.S. Nair et al. 2022). For the study, 100 respondents were approached, and 71 responded, the response rate was 71%.

## Tools Used For The Study

The SPSS version 27.0.1 is used for the analysis of the study. The first hypothesis analyses whether cognitive biases influence the volume of trade done by the investor. The regression analysis is used for testing the first hypothesis. The regression analysis is used to determine the nature of the relationship between two variables (H. Bhandari, 2019).

## Secondary Data Sources

Various journals, articles, newspaper articles, and government publications are examined to understand the concepts of gamification and its impact on retail investors in India.

## Data Analysis

### Descriptive Analysis

### A) Respondent Analysis

Seventy-one investors were selected for the study, with a median age of 34 and a range of 40, the highest age being 64 and the lowest age being 24. Most respondents work in the private sector or are involved in freelance/casual jobs. The median income received by the respondents is 18214 Indian rupees. The respondents have an average experience of 3.6 years.

**Table 1: Age Of The Respondents**

| | |
|---|---|
| N | 71 |
| Mean | 33.79 |
| Median | 34.00 |
| Std. Deviation | 10.457 |
| Range | 40 |

**Table 2: Investment Experience**

| | |
|---|---|
| N | 71 |
| Mean | 3.6303 |
| Median | 2.0000 |
| Std. Deviation | 3.75211 |
| Range | 18 |

**Table 3: Cross-tabulation Of Monthly Income And Occupation Of The Respondents**

| | | Monthly Income | | | | | Total |
|---|---|---|---|---|---|---|---|
| | | 15000 or below | 15000-25000 | 25000-35000 | 35000-45000 | Above 45000 | |
| Occupation | Business | 1 | 1 | 0 | 0 | 1 | 3 |
| | Freelance / Casual Labour | 14 | 3 | 0 | 0 | 1 | 18 |
| | Government Sector | 0 | 0 | 1 | 3 | 6 | 10 |
| | Private Sector | 16 | 10 | 7 | 2 | 5 | 40 |
| Total | 31 | 14 | 8 | 5 | 13 | 71 | |

**b) Likert Scale Analysis**

The behavioural biases are measured using a five-point Likert scale. The behavioural biases taken for the study are- Availability Heuristics, Loss Aversion, Anchoring, Herding and Overconfidence bias. The responses from the Likert scale are averaged to derive the scores of the biases.

**Table 4: Descriptive Analysis Of Behavioural Biases**

| | Availability | Loss Aversion | Anchoring | Herding | Overconfidence |
|---|---|---|---|---|---|
| Mean | 3.6486 | 3.3296 | 3.4690 | 3.3577 | 3.5380 |
| Median | 3.7500 | 3.2000 | 3.5000 | 3.2000 | 3.4000 |
| Std. Deviation | .72698 | .77245 | .73613 | .65980 | .67662 |

**Linear Regression Model**

The first hypothesis is tested using the multiple linear regression model. The dependent variable is the volume of trade, which is the total number of transactions of an investor in each period. The period selected for the study was three months, from April 2023 to July 2023. The independent variables are the behavioural biases. The summary of results from the regression analysis is given below:

**Table 5: Regression Model Summary**

| R | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson |
|---|---|---|---|---|
| .800 | .641 | .613 | 1.257 | 2.146 |

Table 5 shows the model summary. It provides the information about the percentage of variation in the independent variable explained by the independent variable ($R^2$ and Adjusted $R^2$), the standard error of the model and the Durbin-Watson Autocorrelation Statistic. The present model can explain 64% of the variation in the dependent variable (volume of trade). The standard error is 1.257, and the D-stat is 2.146; a value close to 2 implies that the model has low Autocorrelation.

**Table 6: Regression Coefficients**

| Unstandardized Coefficients | | | Standardized Coefficients | t | Sig. | Collinearity Statistics |
|---|---|---|---|---|---|---|
| B | | Std. Error | Beta | | | VIF |
| (Constant) | -6.561 | 1.297 | | -5.057 | .000 | |
| Availability | .727 | .219 | .262 | 3.328 | .001 | 1.118 |
| Loss Aversion | .676 | .217 | .258 | 3.122 | .003 | 1.241 |
| Anchoring | .646 | .208 | .235 | 3.105 | .003 | 1.040 |
| Herding | .821 | .272 | .268 | 3.023 | .004 | 1.422 |
| Overconfidence | .958 | .238 | .321 | 4.027 | .000 | 1.148 |

Table 6 shows the regression coefficients, their p-value, and the multicollinearity statistic. The regression coefficient for Availability is 0.727, loss aversion is 0.676, anchoring is 0.646, Herding is 0.821, and overconfidence bias is 0.958. All the coefficients are statistically significant since the p-values of all the estimators are less than 0.05. The Variation inflation factor (VIF) checks the presence of multicollinearity in the data. The VIF ratio is between 1 and 1.5 for all coefficients, indicating low multicollinearity among the independent variables.

The heteroscedasticity of the data is measured using the Breusch-Pagan test. The null hypothesis states that there is no heteroscedasticity. The results of the test are given below:

**Table 7: Breusch-Pagan Test For Heteroskedasticity**

| Chi-Square | df | Sig. |
|---|---|---|
| 1.465 | 1 | .226 |

Table 7 provides the results of Breusch-Pagan Test for Heteroskedasticity. The level of significance is 0.226, which is greater than 0.05, indicating there is no heteroscedasticity in the data. Thus, the regression coefficients obtained from the data are significant and free of autocorrelation, multicollinearity, and heteroscedasticity. The regression equation can be written as:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + u$$

Volume of trade = -6.561 + 0.727 Availability +0.676 Loss Aversion + 0.646 Anchoring+ 0.821 Herding +0.958 overconfidence + $u_i$

**FINDINGS AND DISCUSSION**

The present study has two goals: to identify the common behavioural biases used by the gamified trading platforms and their extent of influence on the volume of trade of investors. The cognitive biases were selected after conducting an extensive literature review. The chosen biases are Availability Heuristics, Loss Aversion, Anchoring, Herding, and overconfidence bias.

The second part of the study focuses on the effect of these biases on the buying decisions of the investor. For this purpose, data were collected from 71 retail investors living in and around Kerala. A multiple regression analysis has been conducted, where the dependent variable is the volume of trade of the investor, and the independent variables are the cognitive biases. The results from the analysis state that all the parameters chosen are statistically significant with a p-value < 0.05. The beta coefficient of availability is 0.727, loss aversion is 0.676, anchoring is 0.646, herding is 0.821, and overconfidence bias is 0.958. The model has a high R2 value of 0.64 and an Adjusted R2 value of 0.613. Therefore, it can be concluded that behavioural biases significantly influence the volume of trade done by them.

**CONCLUSION**

The role of behavioural biases in the investment decisions have been studied extensively but the role of mobile applications and gamification is a relatively new spectrum in behavioural finances. The study focuses on retail investors of Kerala, a state of India and the cognitive biases that influence their gamified trading application usage and investment pattern. Five biases were selected as independent variable after conducting extensive literature and review, they are: Availability heuristics, loss aversion, anchoring, herding and overconfidence bias. Multiple linear regression analysis was conducted and the results were significant. All the parameters are positively related to the dependent variable; the parameters herding and overconfidence have a higher influence on the volume of trade of the investors compared to other parameters. A high correlation between overconfidence and volume of trade can be attributed to the past investment success of the investor through the apps (Kumar, J. & Prince, N, 2022) and the oversimplified nature of the applications (Cozby, M. 2023).

The herding behaviour has the second highest influence on the volume of trade of the investor. The presence of social media has increased the herding behaviour of the individuals, it influences the decision making of the investors as well (Abu-Taleb, S.K & Nilsson F, 2021). The trading apps using their algorithm promote stocks that are popular among their users' demographic, creating an illusion that they are popular and investing on it yields higher return in future (Baddley, M. 2020).

Availability heuristics has the third highest explanatory power. The investors often form their decision based on the recent information received by them (Nofsinger, J & Varma, A, 2023). The availability heuristics is applied similarly to the anchoring bias by the trading apps. The algorithm of these platforms utilizes the information given by the user to provide personalized stocks (Chaudhary and Kulkarni, 2021). The analytics feature of these applications simplifies the information about the stock concisely and understandably. The decisions taken by the investors are significantly influenced by the information from the analytics of the applications.

The loss aversion bias, though relatively less in terms of explanatory power, has a positive relationship with the volume trade of the investor. The gamified applications provide rewards and discounts for the users who use the application consistently to make investments. Breaking this streak even for a day would result in no rewards (Yu-kai Chou, 2015). The investors consider these rewards as something they earned rather than something they were provided as a part of the app's service (Rawley J. et al., 2021). Therefore, they choose not to lose the rewards they 'earned' by stopping using the app. The gamified trading platforms use this technique to keep users continuing their investments.

The anchoring bias has the lowest explanatory power among all the parameters. Anchoring is used by the gamified platforms in a nuanced manner, using local leaderboards and providing news about the stock market. The leaderboards will act as an anchor point for the investors and form their decisions. (Song, S., 2022). The apps provide news and updates about the stock market, and this information is used as an anchor to the investor's decision-making.

## Limitations

The study was conducted through the questionnaire method, where the researcher sent the questionnaires to the respondents through e-mail and other sources. Therefore, there are chances for bias in the data from the respondents. There were time and resource constraints while conducting the study. The study was limited to the state of Kerala, India.

## Scope For Further Studies

The growth of trading applications boosted the number of stock traders in the country. To maintain the user interest, the applications use the gamified trading principles. They are the behavioural biases that affect an individual's decision-making abilities. The current study is conducted in the initial phase of the expansion of these applications. The possibilities of elaborate research on the future of gamification, ethical concerns, its effects on market volatility etc.

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