DOI: http://doi.org/10.4038/ijabf.v8i2.129

International Journal of Accounting & Business Finance

Vol.8, No.2, December 2022 Issue. pp.157 - 180

QUANTIFYING BEHAVIORAL BIASNESS IN INVESTMENT DECISIONS WITH SPECIAL REFERENCE TO UTTAR PRADESH

Agarwal, A.[1] and Sushma[2]

[1]*Rajkiya Engineering College, Kannauj, Uttar Pradesh, India.*

[2]*Institute of Management Sciences, University of Lucknow, Lucknow, Uttar Pradesh, India.*

Received: June 24, 2022 Revised: October 16, 2022 Accepted: December 25, 2022

Abstract

Behavioral biases haven't gotten the attention they merit, especially in the Indian context. Despite the abundance of information on behavioural finance, only a few academic research has sought to examine behavioural biases across different demographic groups. This research tries to address this lacuna in the literature. The present research work aims to investigate and quantify the behavioural biases that influence individual investors' investment decisions. The primary data was collected through a structured questionnaire from five prominent cities in the most populated state of India, i.e., Uttar Pradesh. The data was collected from 487 individual investors with the help of their financial advisors and brokers. The empirical research work revealed that eight listed biases affect investment decisions by nearly 82%. The outcome as a formal bias assessment instrument was supported by exploratory factor analysis (EFA) encompassing eight behavioural biases measured via 47 statements. The present research contribution, provides a formal assessment tool and further helps the researchers to uncover behavioral biases and develop de-biasing strategies. Academicians, financial advisers, practitioners, and economic psychologists are invited to utilize the instrument in order to further confirm its efficacy.

Keywords: Behavioral Biases, Exploratory Factor Analysis (EFA), Investment Decisions

1. Introduction

The traditional model of finance presupposes that investors and markets are rational (Kumar & Goyal, 2015). They take into account all of the information before making any investments. When it comes to making decisions about their finances, investors frequently veer from reasonable thought (Nigam et al., 2018; Tourani et al., 2005). They base their choices on their ideas and belief-system, their tastes, or the experiences they've had in the past. On the other hand, under situation of uncertainty, investors tend to make decisions that are irrational, inconsistent, and incompetent (Barros, 2010; Kahneman & Tversky, 1982; Stracca, 2004). Behavioral finance appeared in 1990s journals, newspapers, and business publications. Psychology, sociology, and finance inspired this field of finance. Behavioral

Corresponding e-mail:drakashagarwal@reck.ac.in

finance discusses how psychological flaws affect investor decision-making to better interpret investor behaviour. Daniel et al. (1998) say investors don't always make sensible decisions. Behavioral biases influence investors' cognitive and emotional decisions. Any decision (financial or non-financial) is influenced by demographic, socio-economic, and psychological aspects (Bashir et al., 2013). Researchers observed that decision makers can act rationally or irrationally (Chira et al., 2008). Behavioral finance helps explain illogical decisions. Hirshleifer (2015) found that behavioural finance can help individuals make better financial decisions by satisfying psychological demands. Behavioral finance combines economics, finance, and psychology (Zindel et al., 2014).

The vast majority of the studies that have been conducted on the subject of behavioural finance have made extensive use of the information gleaned from the trading history of various individuals (Chen et al., 2007). However, primary data serves as a more accurate predictor of the actions taken by investors when compared to secondary data (Lin, 2011). Emotions and psychology are part of behavioural finance (Lucarelli & Brighetti, 2011). It helped interpret and justify irrational judgments made in key situations. Behavioral finance theories can help individuals (Jordan et al., 2015).

Therefore, the purpose of this research is to fill this gap by making use of primary data and concentrating primarily on the cognitive biases of individual investors because of the important role they play in India (Ramadorai, 2013). The purpose of the study is to empirically contribute by developing a scale that can measure the behavioural biases that are associated with individual investors.

2. Literature Review

Behavioral biases that influence investment decisions have been studied, investigated and explored by psychologists earlier. Various financial judgments, according to studies, are influenced by an individual emotions and are associated with universal needs, fear, greed, and so on. Over time, various studies have been carried out to measure these behavioural biases. Behavioral finance contends that decisions are formed through the use of mental shortcuts known as heuristics or behavioural biases, in contrast to the assumption of rationality and complete knowledge that is present in classical finance (Barber & Odean, 2001; Kahneman & Tversky, 1982). Cognitive and emotional biases are the two categories of behavioural biases that have been identified in academic research (Kengatharan & Kengatharan, 2014; Pompian, 2006; Sahi et al., 2013). Cognitive biases can be introduced through errors in statistical analysis, processing, or memory. The flawed reasoning that is caused by emotional instincts is what gives rise to emotional biases (Pompian, 2006). In this study, eight prevalent behavioural biases were investigated. Individual investors' decisions are influenced by these eight types of bias.

Table 1 *(please refer to the annexure)* gives a brief description of each bias under consideration, along with a list of its major contributors. The statements used to obtain primary data via questionnaire are also included in Table 1. As a result, both the assertion in question and the supporting evidence are presented in Table 1 clearly. These biases were discovered to be connected to the strength of human character and to be crucial in the development of the human self. Behavioral biases have been found to influence almost all types of investors in some way.

Waweru et al. (2008) classified different behavioral biases into three major domains, as shown in Table 2 here as:

- Biases related to prospect and framing factors (that includes representativeness, overconfidence, anchoring, gamblers fallacy and availability bias)
- Biases caused by heuristics (includes mental accounting, loss and regret aversion)
- Additional biases (Herding bias)

Table 2 - Classification of biases

Group	*Behavioral variables*
Heuristic Theory	- Representativeness
	- Overconfidence
	- Anchoring
	- Gambler's fallacy
	- Availability Bias
Prospect Theory	- Loss aversion
	- Regret aversion
	- Mental accounting
Herding Effect	- Buying and Selling decisions of other investors

Source: Waweru et al. (2008)

2.1. Representative Bias

Heuristics have been found to be associated largely with investment decisions. Tversky and Kahneman (1974) Representativeness implies that decisions are made on the basis of stereotypes. It causes people to look for things in the same way that others do. According to studies, investment decisions involving this bias are based on perceptions of patterns that may or may not exist in reality. Abreu (2014); Kannadhasan (2009) define representativeness as a situation in which an investor tends to buy the 'hot' stocks (which are currently in the news due to their performance) while avoiding the poor or low performing stocks. According

Vol.8, No.2, December 2022 Issue. pp.157 - 180

to De Bondt and Thaler (1995), this behavior explains why investors overreact. They conclude that representativeness leads individuals to believe that recent trends are repetitive in nature, causing investors to overreact. This bias, according to Tversky and Kahneman (1973), can be identified by performing the following actions:

- Investors attempt to create patterns from recent investment data.
- Attempts are made by investors to forecast or extrapolate past returns.
- Investors prefer investments with a strong track record because they are representing well-performing funds.
- Investors are overly optimistic about past winners.
- Investors are victims of the good company-good stock syndrome.

2.2. Gambler's Fallacy:-

The name comes from the assumption that gambling is associated with a belief that one will always win. Individuals incorrectly predict past trend movements and future realignments (Thaler & Johnson, 1990). The investor anticipates that the event will reoccur in the near future. Gambler's fallacy is incorrectly predicting a trend's reversal with the same probability (Barberis & Thaler, 2003).

2.3. Overconfidence

Overconfidence confirms individual conduct and drives the person to defend his incorrect action to its logical conclusion (Odean, 1998b). Women are less confident than men, hence they invest less (Barber & Odean, 2001). Overconfident people underestimate their error margins (Shiller, 2005). Irrational investors suffer from overconfidence bias because they are overconfident in their philosophies and judgments (Barber & Odean, 2000). These people misjudge their abilities and strongly believe in their basic views and skills.

2.4. Availability Bias

Humans tend to judge the likelihood of an event based on how easily relevant information can be remembered. Tversky and Kahneman (1973) proposed a method for obtaining all relevant information about an event by noting all associated and concatenated information as eight or more points. The investor is also influenced by how easily they can compile or gather all relevant information (Barberis & Shleifer, 2003). Investment decisions are influenced by readily available market information.

Vol.8, No.2, December 2022 Issue. pp.157 - 180

2.5. Loss Aversion

Loss aversion is a behavioural circumstance observed in an individual’s decision making under risk and enigma. Individuals who are affected by this bias are found to be more susceptible to losses than gains. Tversky and Kahneman (1974) explained loss aversion as a subset of Prospect Theory. People with this bias don't want to accept losses easily. Shefrin and Statman (2000) call this "Get-even-itis," where a person believes the market performs according to their benefits and exits investments before incurring higher losses. Loss aversion measures whether a loss's mental penalty is greater than a gain's. Humans go to extremes to avoid losses, which reduces their achievement rate (Shiller, 2005). Human attitudes toward risks and rewards may vary from those toward losses.

2.6. Regret Aversion

The regret aversion bias is a sentimental tendency to overlook bad decisions. Tversky and Kahneman (1981) explained that each individual’s decision is ultimately lined with two different emotions, i.e., either regret or joy. Regret expresses displeasure, while joy at a decision expresses joy. Regret-averse people are risk-averse. Pompian (2008) investigated how a person tries to avoid making risky decisions because it may give them a sense of displeasure or disappointment in the future. According to his theory, people fear that their decision may be wrong, so they exclude alternatives.

2.7. Mental Accounting

Richard Thaler proposed the concept of mental accounting in 1985. According to traditional theories, financial decisions should be based on rational calculations, but people lack such computational and analytical skills. They lack the willpower to evaluate decisions critically. People here categories their wealth into various mental accounts, having a different level of significance (Thaler & Johnson, 1990). This bias explains the human propensity to classify funds into separate mental accounts based on perceived attributes and source of generation. These "mental accounts" are generally divided into separate buckets based on risks (De Bondt & Thaler, 1995). The process is done based on various subjective criteria like the origin of earning and the intention of using which ultimately cause irrational behavior.

2.8. Herd Behaviour

Herding, i.e., a tendency to blindly follow others, has been studied and evaluated earlier as well. Herd behaviour, or "BHED-CHAAL," is a human psychological trait that affects financial and nonfinancial decisions. Every common or uncommon decision of an individual reflects his or her mind-set and demonstrates whether he or she will be a leader or a follower. A person who copies others may not be creative or innovative, which can lead to life problems. Herd behaviour can be disastrous when making financial decisions. The literature includes studies on stock market herd behaviour. Herd behaviour is an investor's tendency to copy others' investments. It's buying winning stocks (at high prices) and selling losers (at lower prices). Waweru et al. (2008) discovered that investors generally exhibit herd behavior when they are worried.

2.9. Research Gap and Significance of Study

There's a lot of research on behavioural finance and investment biases, but most studies employ secondary data to examine the impact (Barber & Odean, 2001; Chen et al., 2007). This domain lacks a robust and systematic instrument to detect behavioural biases, limiting investigations using primary data. This work aims to build an empirically verified and theoretically supported scale to quantify behavioural biases in the Indian context.

Behavioral finance addresses the investor irrationality observed in market anomalies and economic bubbles, often known as behaviorally biased decisions. Advisors and asset managers must be cognizant of investor biases and mental shortcuts that have the potential to influence investment decisions. Understanding market behaviours might help avoid blunders. Mental, emotional, and cognitive biases might affect the recommendations of financial counsellors. Few academic research has attempted to explore behavioural biases across demographic groups, despite the wealth of evidence on behavioural finance. This research examines conceptual and empirical obstacles to the development of a bias assessment instrument. Researchers have measured behavioural biases in recent years. There is no acknowledged, reliable evaluation scale. This article fills a gap in the academic literature.

3. Methods

The research design used here is exploratory, with each behavioral bias (based on its characteristics) studied in order to generate different items in a specific construct.

3.1. Data Collection

The data has been collected from the most populous state of India, i.e., Uttar Pradesh. Uttar Pradesh alone accounts for nearly 17% of India’s population (around 229 million). Furthermore, considering the limitations of time, money, and resources, the primary data has been collected by using a structured questionnaire from five major cities in Uttar Pradesh. These five cities are strategically located and hold a prominent position from a social,

Vol.8, No.2, December 2022 Issue. pp.157 - 180

cultural, economic, industrial, and financial viewpoint. We termed these five cities as Uttar Pradesh's KAVAL cities (Kanpur, Agra, Varanasi, Allahabad, and Lucknow). It takes nearly ten months to collect the data from these five different cities (from September, 2021, to June, 2022).

At a 95% confidence level and a 5% confidence interval, the required sample size will be 384 for the population (nearly 229 million). The data has been collected from 487 individual investors, which is more than the required sample size of 384. This will help to represent the population and make research results more accurate.

3.2. Sample Size

The sampling technique used in this case is cluster sampling, which divides the entire state population into various clusters based on their population ratio in the last census survey. For collection of data various leading brokers and financial investment advisors have been approached in five heterogeneously populated districts of Uttar Pradesh. Brokers & investment advisors further provided accessibility to their clients for research purpose. Around 3000 questionnaires have been circulated through this process, out of which proximately 800 came back. Data from 487 investors has been finally considered for data analysis after filtering and omitting incomplete information sets. For pilot data analysis 118 responses from investors have been compiled here and the results are interpreted.

3.3. Instrument Designing

Reliability of Data

The degree of consistency between different variables is measured by reliability. It is directly related to the measurement procedure's accuracy. The degree of freedom and unstable error are important considerations in reliability. It is essential in all types of primary researches as it ensures the non-duplicity of dependent and independent items in overall data. Cronbach's α is readily available reliability metric tool. The universally acceptable lower limit for social researches is 0.6; however, in exploratory research, it may be as low as 0.50 (Malhotra, 2010).

Table 3 presents that the overall value of Cronbach's α as 0.63 and **Table 8** explains the individual value of Cronbach's α of particular biases as well. The value is found to be greater than the expected value (0.5) of consideration, confirming that the items used are reliable and consistent enough to be used.

Vol.8, No.2, December 2022 Issue. pp.157 - 180

Table 3 - Statistics for reliability of data

Case Processing Summary	N	%
Valid Cases	487	100
Excluded Cases	0	0
Total Cases	487	100
	Cronbach's α value	0.63
	No of Items	47

Bartlett's Test of Sphericity

Malhotra, (2010) explained this statistical tool for interpreting the relationships between variables. It is used to check the research hypothesis weather variables in the population are correlated or not. Table 4 shows that the value for bartlett's test is significant.

Table 4 - KMO, Bartlett's test value

KMO for sample adequacy.		.940
Bartlett's test of sphericity	Approx. chi-Square	39668.112
	d.f.	1081
	Sig.	.000

Kaiser-Meyer-Olkin Test

The KMO index is used to examine the suitability of factor analysis by accessing sample adequacy. KMO values range between 0 and 1. It is considered that the higher the KMO value (between 0.5 and 1) the more appropriate factor analysis is (Malhotra, 2010). **Table 4** presents that the KMO value for variables is 0.94, which is close to 1. As a result, this value is sufficient and validates the fitness of factor analysis.

Factor Analysis

Exploratory factor analysis is the most reliant technique to reduce large amount of data. This method fetches information from a set of data in terms of relatedness, which is called as "factor" that aids in the generation of constructs. It is used to cut short the large number of interrelated variables (which can cause in multicollinearity) and identify data structure based on the sample's inherent characteristics. Here the data has been gathered from structured questionnaire consisting 47 statements regarding various behavioral biases, measured on a five-point Likert scale. The principal component technique has been used.

Factors Extraction

The factor extraction matrix provides variable loading. The initial matrix explains the connectivity between factors; however, these factors may be found to be associated with many other variables. As a result, it's important to perform rotation of variables which is much simpler and easier to interpret. VARIMAX (i.e., maximum variance factors) is a popular rotation method that focuses on factors with high variance. The extracted factors after rotation are presented in **Table 5** of the study, along with their corresponding factor loadings, and it is discovered that 47 items (having factor loading greater than 0.5) can be used for valid construct designing.

Variance Calculations

The number of factors/constructs that must be extracted from data collected is an important criterion in factor analysis. It is important that the factors extracted as construct must describe maximum variance in the data; hence Eigenvalues are taken into account. The factors having Eigen value greater than one are considered significant, while the remaining as insignificant. The cumulative percentage of variance extracted by the overall factors is used to evaluate the total variance contributed by different factors. The goal is to ensure that all extracted constructs must have an enumerative amount of variance.

Table 6 depicts that the factors extracted from the biases are 8 in number that contributes around **81.8%** of overall variance and that's a good percentage to be considered. In accordance with available literature, these constructs/biases are named representative bias, overconfidence bias, gamblers fallacy, availability bias, herding, loss aversion, regret aversion, and mental accounting. Variables have been extracted using principal component analysis.

Inter Factor Correlation

For valid construct/factor development it is important to reassure that the items in the factor are not replicated and in order to confirm it, an inter factor correlation analysis has been done that shows a lower degree of correlation among factors. Table 7 (please see annexure) shows the lower value of "r" which signifies a weaker degree of relationship among different factors constituted. Hence the biases (constructs) are found to be independent.

Vol.8, No.2, December 2022 Issue. pp.157 - 180

4. Results

Implementing the instrument for first usage in a larger population is the next step after the completion of the pilot research results in order to validate the findings. Here, a population of 487 people from various socioeconomic levels in Uttar Pradesh—300 men and 187 women—is subject to the scale (selected randomly). Mean value comparison approaches have been used to verify that these behavioural biases—extracted through factor analysis—are being applied correctly. The mean value for several gender-based behavioural biases is shown in Table 8 (please refer to the appendix).

Here it can be easily elucidated that heuristic-related biases (representative, overconfidence, gamblers' fallacy, and availability bias) show a higher mean value in males as compared to females, while prospect biases (loss aversion, regret aversion, and mental accounting bias) are found higher in females as compared to males. The results are aligned with the findings of researchers regarding the association between gender and different behavioural biases (Arti et al., 2011; Barberis & Thaler, 2003; Deo & Sundar, 2015; Sushma, 2016).

According to (Deo & Sundar, 2015), males who take more chances are more prone to heuristic biases, whereas females who take fewer risks are more prone to prospect and herding biases.

The variation in investing attitudes based on gender was also studied in the (Arti et al. 2011) study. Herding, loss aversion, and regret aversion are also more common in women than in men, while overconfidence, the gambler's fallacy, representativeness, and other heuristic-related biases are more common in men (Dickason & Ferreira, 2018).

The objective here was to provide an instrument that can aid in the measurement of various behavioural biases in order to analyze their presence in the behaviour of an investor. The tool here will enable researchers to identify numerous behavioural biases in an individual and develop de-biasing procedures. For this purpose, five districts of Uttar Pradesh (denoted as KAVAL, i.e., Kanpur, Agra, Varanasi, Allahabad, and Lucknow) have been targeted for data collection. They are found to have the highest number of small-to-medium investors and to have the heterogeneous population required for the study. The data has been collected via financial advisors who further provided access to their clients. After ensuring the reliability of data, factor analysis has been used to segregate different biases. Each bias has been measured with the help of various questions being asked of the sampled population. These questions were based on the 5-point Likert scale, rated between 1 and 5.

The results have been compiled and presented here in the form of a 47-item instrument that can be useful to interpret 8 different behavioural biases (please refer to table 1 attached as an annexure). This enables individuals in the financial industry and policymakers at the highest level to comprehend the behavioural features of various individuals. In this way, they can provide a better behaviorally modified portfolio to their clients in order to achieve maximum customer satisfaction. Also, they can help investors control their biases and give them ways to get rid of their biases so they don't make irrational decisions.

The measurement instrument provided here can help in measuring eight popular behavioural biases. Out of these eight, four of them (representative, overconfidence, gamblers' fallacy, and availability bias) belong to the heuristic category, and three of them (loss aversion, regret aversion, and mental accounting bias) are found to be from the prospective biases category. The eighth one is herding bias, which is the most popular among studies to date (Waweru et al., 2008).

5. Conclusion

The findings showed that the scale developed to measure behavioural finance contains a variety of different biases. The research investigated a total of eight different behavioural biases. Results support the theories put forth by behavioural finance and psychology researchers (Abreu, 2014, Shefrin & Statman, 2000; Waweru et al., 2008), who contend that flaws brought on by investors' irrational thinking and emotions influence their financial behaviour. The current study supported the notion that investors' decisions are influenced by more than just their reasoning and calculating skills; rather, their emotions have a greater bearing on such decisions (Waweru et al., 2008). The manifestation of availability bias was found to be a powerful indication of cognitive biases. It demonstrates that people seek to avoid the difficulties and suffering brought on by investment choices. Therefore, they analyse the data based on how quickly they can recall it. The connection between the regret-aversion bias and emotional biases shows that individuals may forfeit the potential advantages of investment in order to avoid feeling regret for the decisions they make. As a result of their previous investment experiences, people occasionally stick with their current status quo, but on other occasions, they undergo a transformation and begin actively seeking out or enjoying risk.

This paper makes a contribution to the academic field of behavioural finance by providing a method for measuring a variety of different behavioural biases. The scale helps enhance investing decision-making by drawing attention to the inherent biases of investors. Because of the magnitude, it is advantageous for academics to be able to analyse behavioural biases for which there are fewer studies.

This study employs a comprehensive scale to assess biases and the factors that contribute to them. Financial advisors can use this scale to evaluate the behavioural biases of their clients and offer them personalised recommendations to help them get over their prejudices and improve the performance of their investments. The research challenges preconceived notions by bringing them into the open. The significance of the paper cannot be overstated due to the fact that awareness of bias is essential to the reduction of prejudice. Additionally, the scale can also be utilised to evaluate financial awareness and education programmes that are intended to eliminate the behavioural biases that are exhibited by investors. The scale will help regulators better understand the biassed behaviour of investors in times of market stress, crises, and other situations.

Future research might be able to address some of the issues with this study's methodology. The opinions and input of investors are used to create this scale in its entirety. The scale can be modified and applied to evaluate the behavioural biases of a variety of parties involved in the decision-making process for investments. These parties can include institutional investors, financial advisors, and a variety of other individuals. The responses collected from investors in the five cities of Uttar Pradesh, India's state with the largest population density, are the foundation of the present research report. Responses from various regions of the country should be taken into account in order to validate this scale.

Notes-

Questionnaire Scoring:

Questions from R1 to R6 belong to representative bias, O1 to O6 are from overconfidence bias, G1 to G6 are the one from gamblers fallacy, A1 to A6 belong availability bias, H1 to H6 are herd bias, L1 to L6 are loss aversion bias, RA1 to RA6 belong to regret aversion bias and lastly M1 to M5 are the questions belong to mental accounting bias. (Refer table 01 available in annexure).

The Likert score is calculated on the scale of 1 to 5 as per the respondent's choice and later the average Likert score has been considered for one particular set of questions belonging to a particular bias. The interpretation of score is done as follows:

Average Likert Score= 1: Strongly Unbiased

Average Likert Score= 2: Moderately Unbiased

Average Likert Score= 3: Neither Unbiased nor Biased

Average Likert Score= 4: Moderately Biased

Average Likert Score= 5: Strongly Biased

References

Abreu, M. (2014). Individual investors' behavioral biases Excerto da Lição de Síntese das Provas de Agregação, 1-55. https://www.repository.utl.pt/bitstream/10400.5/7439/1/TEWP012014.pdf

Arti, G., Julee, & Sunita, S. (2011). Difference in Gender Attitude in Investment Decision Making in India. *Research Journal of Finance and Accounting*, *2*(12), 1–6. www.iiste.org

Barber, B. M., & Odean, T. (2000). Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. *The Journal of Finance*, *55*(2), 773–806. https://faculty.haas.berkeley.edu/odean/papers%20current%20versions/individual_investor_performance_final.pdf

Barber, B. M., & Odean, T. (2001). Boys will be boys: gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, *1*(1), 261–292. http://qje.oxfordjournals.org/Downloadedfrom

Barberis, N., & Shleifer, A. (2003). Style investing. *Journal of Financial Economics*, *68*(1), 161–199. https://doi.org/10.1016/S0304-405X(03)00064-3

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, *1*, 1053-1128. https://doi.org/10.1016/S1574-0102(03)01027-6

Barros, G. (2010). Herbert A. Simon and the concept of rationality: boundaries and procedures. *Brazilian Journal of Political Economy*, *30*, 455-472. https://doi.org/10.1590/S0101-31572010000300006

Bashir, T., Javed, A., Butt, A. A., Azam, N., Tanveer, A., & Ansar, I. (2013). An Assessment Study on the "Factors Influencing the Individual Investor Decision Making Behavior". *IOSR Journal of Business and Management*, *9*(5), 37–44. www.iosrjournals.orgwww.iosrjournals.org

Chen, G., Kim, K. A., Nofsinger, J. R., & Rui, O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of behavioral decision making*, *20*(4), 425-451. https://doi.org/10.1002/bdm.561

Chira, I., Adams, M., & Thornton, B. (2011). Behavioral Bias Within The Decision Making Process. *Journal of Business & Economics Research (JBER)*, *6*(8), 11-20. https://doi.org/10.19030/jber.v6i8.2456

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *the Journal of Finance*, *53*(6), 1839-1885. https://doi.org/10.1111/0022-1082.00077

De Bondt, W. F., & Thaler, R. H. (1995). Financial decision-making in markets and firms: A behavioral perspective. *Handbooks in operations research and management science*, *9*, 385-410. https://doi.org/10.1016/S0927-0507(05)80057-X

Deo, M., & Sundar, V. (2015). Gender difference: Investment behavior and risk taking. *SCMS Journal of Indian Management*, *12*(3), 74-88. https://www.researchgate.net/publication/323675760

Dickason, Z., & Ferreira, S. (2018). Establishing a link between risk tolerance, investor personality and behavioral finance in South Africa. *Cogent Economics and Finance*, *6*(1), 1–13. https://doi.org/10.1080/23322039.2018.1519898

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383-417. https://faculty.haas.berkeley.edu/odean/papers%20current%20versions/individual_investor_performance_final.pdf

Fama, E. F., & French, K. R. (1992). American Finance Association Wiley The Cross-Section of Expected Stock Returns. *Source: The Journal of Finance*, *47*(2), 427–465. http://www.jstor.orgURL:http://www.jstor.org/stable/2329112http://www.jstor.org/stable/2329112?seq=1&cid=pdf-reference#references_tab_contents

Hirshleifer, D. (2015). Behavioral Finance. *Annual Review of Financial Economics*, *7*(1), 133–159. https://doi.org/10.1146/annurev-financial-092214-043752

Jordan, B., Miller, T., & Dolvin, S. (2015). *Fundamental of Investments: Valuation and Management* (7th ed.). McGraw Hill.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–292. https://doi.org/10.1017/CBO9780511803475.003

Kahneman, D., & Tversky, A. (1982). The psychology of preferences. *Scientific American*, *246*(1), 160-173. https://doi.org/10.1038/scientificamerican0182-160

Kengatharan, L., & Kengatharan, N. (2014). The Influence of Behavioral Factors in Making Investment Decisions and Performance: Study on Investors of Colombo Stock Exchange, Sri Lanka. *Asian Journal of Finance & Accounting*, *6*(1), 1-23. https://doi.org/10.5296/ajfa.v6i1.4893

Kumar, S., & Goyal, N. (2015). Behavioural biases in investment decision making – a systematic literature review. *Qualitative Research in Financial Markets*, *7*(1), 88–108. https://doi.org/10.1108/QRFM-07-2014-0022

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of financial economics*, *32*(1), 23-43. https://scholar.harvard.edu/files/shleifer/files/impact_instit_trading.pdf

Malhotra, N. K., & Dash, S. J. M. R. (2010). An applied orientation. *Marketing Research*, *2*. http://wwwfp.pearsonhighered.com/assets/hip/gb/hip_gb_pearsonhighered/preface/013473484X.pdf

Nigam, R. M., Srivastava, S., & Banwet, D. K. (2018). Behavioral mediators of financial decision making – a state-of-art literature review. *Review of Behavioral Finance*, *10*(1), 2-41. https://doi.org/10.1108/RBF-07-2016-0047

Odean, T. (1998a). Are investors reluctant to realize their losses? *Journal of Finance*, *53*(5), 1775–1798. https://doi.org/10.1111/0022-1082.00072

Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. *The journal of finance*, *53*(6), 1887-1934. https://doi.org/10.1111/0022-1082.00078f

Pompian, M. M. (2008). Using behavioral investor types to build better relationships with your clients. *Journal of Financial Planning*, *21*(10), 64-76. https://sunpointeinvestments.com/wp-content/uploads/UsingBehavioralInvestorTypestoBuildBetterRelationshipswithclients.pdf

Rushdi, N. J., & Sushma. (2019). Establishing AN Association between Risk Tolerance and Behavioral Biases among Indian Investors. *International Journal of Engineering and Advanced Technology*, *9*(2), 1378–1382. https://doi.org/10.35940/ijeat.B2637.129219

Shefrin, H., & Statman, M. (2000). Behavioral Portfolio Theory. *The Journal of Financial and Quantitative Analysis*, *35*(2), 127-151. https://doi.org/10.2307/2676187

Shiller, R. J. (2005). *Irrational Exuberance* (2nd ed.). Princeton University Press.

Stracca, L. (2004). Behavioral finance and asset prices: Where do we stand? *Journal of Economic Psychology*, *25*(3), 373-405. https://doi.org/10.1016/S0167-4870(03)00055-2

Statman, M. (1999). Behavioral Finance: Past Battles and Future Engagements. *Financial Analysts Journal*, *55*(6), 18–27. https://doi.org/10.2469/faj.v55.n6.2311

Sushma. (2016). Is gender act as an antecedent in developing behavioral biases among investors? *National Journal of Motilal Rastogi School of Management*, *9*(1), 1–5.

Sushma. (2021). *A study on behavioral biases and its impact on financial risk tolerance among investors of Uttar Pradesh.* [Dr. APJ Abdul Kalam Technical University]. https://shodhganga.inflibnet.ac.in/handle/10603/336422

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice. *Management Science*, *36*(6), 643-660. https://doi.org/10.1287/mnsc.36.6.643

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management science*, *36*(6), 643-660. https://doi.org/10.1111/j.1467-629x.2004.00131.x

Tversky, A., & Kahneman, D. (1971). Belief in the law of small numbers. *Psychological bulletin*, *76*(2), 105-110. http://stats.org.uk/statistical-inference/TverskyKahneman1971.pdf

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive psychology*, *5*(2), 207-232. https://familyvest.com/wp-content/uploads/2019/02/TverskyKahneman73.pdf

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157) , 1124-1131. https://doi.org/10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (1981). VThe framing of decisions and the psychology of choice. *Science*, *211*(4481), 453-458. www.sciencemag.org

Waweru, N. M., Munyoki, E., & Uliana, E. (2008). The effects of behavioural factors in investment decision-making: a survey of institutional investors operating at the Nairobi Stock Exchange. *International Journal of Business and Emerging Markets*, *1*(1), 24-41. https://econpapers.repec.org/RePEc:ids:ijbema:v:1:y:2008:i:1:p:24-41

Zindel, M. L., Zindel, T., & Quirino, M. G. (2014). Cognitive bias and their implications on the financial market. *International Journal of Engineering and Technology*, *14*(3), 11-17.

Vol.8, No.2, December 2022 Issue. pp.157 - 180

Annexure and Tables

Table 1

Behavioral Biases and their Contributors:

Behavioral Biases	Statements (Items)		Major Contributors
Representativeness	R1.	I try to generate a pattern in previous earnings and losses to use it as a trend for future.	• Dhar and Kumar (2001), • Kaestner (2005) • Tversky and Kahneman (1974),
	R 2.	I can do correct predictions regarding future returns on the basis of past.	
	R 3.	I believe that I can predict the situations of global financial crisis in advance.	
	R 4.	I believe correct forecast always depend on earlier studies.	
	R 5.	I can take investment decisions on the basis of previous market trends.	
	R 6.	My predictions always proven me correct regarding financial investments.	
Overconfidence	O7.	I trust my capabilities to manage new investment portfolios.	• Alpert and Raiffa (1984), • Barber and Odean (2000), • Fischhoff, Solvic and Lichtenstein (1977), • Gervais and Odean (2001) • Odean (1998), • Tversky (1990), • Wood (1996),
	O 8.	My previous successful investments have boosted my confidence.	
	O 9.	I feel that my earlier investment assumptions have proven correct.	
	O 10.	I believe that my investment options had outperformed in past.	
	O 11.	I rely on my analytical skills to evaluate all decisions myself.	
	O 12.	I feel that my investment skills provide me an extra edge to earn profits.	
Gamblers Fallacy	G13.	I sometimes invest just for the fun and excitement.	• Barberis (2003),

Vol.8, No.2, December 2022 Issue. pp.157 - 180

	G14.	At times I am willing to take substantially higher risks in order to get more returns.	• Lucarelli and Brighetti (2011), • Odean(1998), • Richard Thaler (1999) • Singh and Sudhir(2012), • Tversky and Kahneman (1974), • Waweru et al. (2008)
	G15.	My gut feeling and intuition helped me to take decisions in dilemma situations.	
	G16.	I do not hesitate to use even illegal means to earn extra.	
	G17.	I sometimes take advantage of policy loopholes to maximize profits.	
	G18.	I never hesitate to try my luck in earnings.	
Availability Bias	A19.	I avoid investment options which are complicated and difficult to understand.	• Kliger and Kudryavtsev (2010), • Odean(1998) • Singh and Sudhir (2012), • Tversky and Kahneman (1973, 1974),
	A20.	Sometimes I take shortcuts to earn high.	
	A21.	I am more likely to invest in the instruments which are well known and information is readily available.	
	A22.	I believe that my close friends and relatives are a reliable source of information.	
	A23.	I try to opt for recently popular/in-news investment options.	
	A24.	I believe that most popular investment instruments are safer one.	
Herd Behavior	H25.	I get influenced by media reports regarding investment decision.	• Christie and Huang (1995) • Lakonishok et al. (1991), • Scharfstein and Stein (1990),
	H26.	I rely on expert's recommendations while making investments.	
	H27.	The opinion of my close one is important to take investment decision.	
	H28.	I try to copy the investment patter of other investors, if it is less risky.	
	H29.	I always do not have first-hand information to take independent decision.	

	H30.	I feel myself sensitive towards rumours regarding my investments.	
Loss Aversion	L31.	I would rather hold investments instead of taking a loss.	• Coval and Shumway (2003), • Hwang and Satchell (2010) • Kahneman and Tversky (1979), • Lebaron (1999), • Rothschild and Stiglitz(1970),
	L32.	I sometimes go for trying those instrument avenues which has given me poor returns in past.	
	L33.	I am more likely to invest in those instruments which has given higher returns in past.	
	L34.	I am more likely to avoid risk than usual; after getting a loss.	
	L35.	I generally adjust my investments at the time of tax calculation in order to get benefits.	
	L36.	I found myself more sensitive towards losses than gains.	
Regret Aversion	RA37.	I sometimes regret my previous investments.	• Berkelaar and Kouwenberg (2008), • Filbesk et al. (2005), • Hwang and Satchell (2010), • Shefrin and Statman (2011)
	RA38.	The losses on investment decisions give me displeasure.	
	RA39.	The profits on investment decisions give me happiness.	
	RA40.	I sometimes try for past gainer investment avenues.	
	RA41.	I try to avoid those investment avenues which were past losers.	
	RA42.	I try to take help from consultancies after getting losses.	
Mental Accounting	M43.	If I get an amount as a gift, I go for investing in high risky options.	• Barberis and Huang (2001) • Shefrin (1981), • Shiller (1998), • Thaler (1999),
	M44.	I manage my investment options separately and not as a whole portfolio.	
	M45.	I am likely to differentiate between capital appreciation and regular income investment	

Vol.8, No.2, December 2022 Issue. pp.157 - 180

	options.	• Tversky (1999),
M46.	When I receive high profit margin, I tend to hold investment to get even higher profits.	
M47.	I feel that investment options safe that provide good return in long run.	

Table 5

Tabular presentation of factors loadings (rotated):

Items		Components							
		1	2	3	4	5	6	7	8
Item 1	R1	0.615							
Item 2	R2	0.614							
Item 3	R3	0.617							
Item 4	R4	0.61							
Item 5	R5	0.696							
Item 6	R6	0.632							
Item 7	O1		0.702						
Item 8	O2		0.829						
Item 9	O3		0.898						
Item 10	O4		0.898						
Item 11	O5		0.855						
Item 12	O6		0.913						
Item 13	G1			0.917					
Item 14	G2			0.914					
Item 15	G3			0.902					
Item 16	G4			0.901					
Item 17	G5			0.904					
Item 18	G6			0.727					
Item 19	A1				0.729				
Item 20	A2				0.824				
Item 21	A3				0.852				
Item 22	A4				0.812				
Item 23	A5				0.862				

Item 24	A6	0.769				
Item 25	L1		0.894			
Item 26	L2		0.788			
Item 27	L3		0.772			
Item 28	L4		0.9			
Item 29	L5		0.891			
Item 30	L6		0.868			
Item 31	RA1			0.861		
Item 32	RA2			0.641		
Item 33	RA3			0.744		
Item 34	RA4			0.819		
Item 35	RA5			0.957		
Item 36	RA6			0.799		
Item 37	H1				0.739	
Item 38	H2				0.94	
Item 39	H3				0.815	
Item 40	H4				0.895	
Item 41	H5				0.919	
Item 42	H6				0.93	
Item 43	M1					0.791
Item 44	M2					0.762
Item 45	M3					0.649
Item 46	M4					0.758
Item 47	M5					0.829

Extraction Method: PCA

Table 6

Variance of factors:

Co	Initial Eigen value	Extracted Sums of Square	Rotated Sums of Square

mp one nts	Total	Varian ce % ag e	Cumula tive %ag e	Total	Varian ce %a ge	Cumula tive %a ge	Total	Varianc e %a ge	Cumula tive %ag e
1	25.939	55.19 0	55.190	25.93 9	55.190	55.190	19.079	40.593	40.593
2	3.709	7.892	63.082	3.709	7.892	63.082	6.025	12.819	53.413
3	2.189	4.657	67.739	2.189	4.657	67.739	5.172	11.004	64.416
4	1.666	3.545	71.284	1.666	3.545	71.284	2.645	5.629	70.045
5	1.425	3.032	74.316	1.425	3.032	74.316	1.654	3.519	73.564
6	1.285	2.735	77.051	1.285	2.735	77.051	1.331	2.831	76.395
7	1.135	2.416	79.467	1.135	2.416	79.467	1.311	2.789	79.184
8	1.101	2.342	81.809	1.101	2.342	81.809	1.233	2.624	81.809
9	.978	2.081	83.890						
10	.864	1.838	85.728						
11	.836	1.779	87.508						
12	.698	1.486	88.993						
13	.622	1.323	90.316						
14	.549	1.168	91.485						
15	.501	1.066	92.551						
16	.392	.835	93.386						
17	.377	.803	94.189						
18	.291	.620	94.809						
19	.284	.605	95.414						
20	.239	.508	95.922						
21	.215	.457	96.379						
22	.199	.424	96.803						
23	.192	.409	97.212						
24	.153	.327	97.539						
25	.147	.313	97.852						
26	.111	.237	98.088						

27	.093	.199	98.287
28	.092	.195	98.482
29	.086	.182	98.664
30	.078	.165	98.829
31	.076	.162	98.991
32	.070	.150	99.141
33	.059	.126	99.267
34	.054	.114	99.382
35	.049	.104	99.486
36	.040	.085	99.570
37	.034	.073	99.643
38	.031	.065	99.708
39	.027	.057	99.766
40	.022	.046	99.812
41	.018	.039	99.851
42	.015	.032	99.883
43	.014	.029	99.912
44	.012	.025	99.937
45	.010	.022	99.959
46	.010	.022	99.980
47	.009	.020	100.000

Extraction Method: PCA.

Table 7

Inter Factor Correlation

Correlations

Variables	Representativeness	Overconfidence	Gamblers_Fallacy	Availability	Loss_Aversion	Regret_Aversion	Herd	Mental_Accounting
Representativeness	1.000	.343	.107	.368	-.189	.144	.290	.278
Overconfidence	.343	1.000	.675	.400	-.311	-.141	-.235	-.282
Gamblers_Fallacy	.107	.675	1.000	.466	-.087	.025	-.203	-.296
Availability	.368	.400	.466	1.000	.058	.062	-.149	.006
Loss_Aversion	-.189	-.311	-.087	.058	1.000	.589	.144	.216
Regret_Aversion	.144	-.141	.025	.062	.589	1.000	.269	.272
Herd	.290	-.235	-.203	-.149	.144	.269	1.000	.251
Mental_Accounting	.278	-.282	-.296	.006	.216	.272	.251	1.000

Table 8

Mean Values associated with Gender

Gender		**Male**			**Female**			**Total**		
	Cronbach's α	Mean	N	Std. Dev.	Mean	N	Std. Dev.	Mean	N	Std.Dev.
Representativeness	0.909	3.43		0.47	2.80		0.89	3.19		0.73
Overconfidence	0.857	3.51		0.58	2.93		0.89	3.29		0.77
Gamblers_Fallacy	0.971	3.47	300	0.75	2.79	187	1.24	3.21	487	1.02
Availability	0.945	3.27		0.76	2.94		0.92	3.14		0.84
Loss_Aversion	0.722	2.67		0.44	2.94		0.82	2.78		0.63
Regret_Aversion	0.719	2.61		0.52	3.03		0.77	2.77		0.66

Herd	0.731	2.12	0.59	2.95	0.78	2.44	0.78
Mental_Accounting	0.582	2.95	0.54	3.24	0.79	3.06	0.66