Behavioral Attributes Influencing Decision Making of Indian Derivative Market Investors

ABSTRACT:

Aim: The retail investors of the Indian investment landscape are found to base their investment decisions on several factors that may not be entirely attributed to price movement and information availability. Various studies have been conducted to capture these behavioral attributes that may invariably have an influencing effect either knowingly or unknowingly on the investors. This study aims to identify these behavioral biases influencing investor's decision-making when they are active participants in the Indian Derivative market.

Methodology: The study is conducted using primary data over 200 derivative investors within the northern Indian subcontinent aged between 18 years to 50 years. A questionnaire has been adapted from the defined scales from literature and uses the Likert scale to measure the behavioral patterns of investors. A cross-sectional survey method is used to distribute the questionnaire both online and offline. Factor analysis is then employed to identify the latent variables impacting the decision-making.

Results: The sample under study generated six factors that have a significant influence on decision-making. These factors include Herding bias, Overconfidence bias, Risk Aversion, Market Responsiveness, Information processing Style and Information Reliance. All these factors have a significant influence on the investors buying and selling behavior in the Indian derivative market. A reliability test was run to assess the reliability of the factors where the Cronbach alpha was found to be above 0.8 for all the factors which shows a strong internal coherence among the factors.

KEYWORD:

Behavioural Finance, Biases, Investor Decision, Derivative Market, Indian Retail Investors, Factor Analysis

INTRODUCTION:

Given the impending transformation in the economy and the introduction of new streams and products in the market, this era could be deemed prosperous for the Indian industries. The supportive government regulations and policies have fostered industry growth, resulting in a rise in the capital needs of the Indian economy and subsequently boosting stock market returns.

Presently, investors are confronted with the dilemma of choice from a wide array of investment options. Given the abundant investment opportunities and the promising return prospects in the market, individuals often find themselves overwhelmed by the surplus of choices, resulting in a state of perplexity and indecision. This dilemma frequently results in postponed investment decisions or even the complete avoidance of certain investment opportunities. Consequently, a pertinent query arises regarding the influence of limitless choices on investment decision-making processes. This is where the discipline of finance comes into the picture.

Since the early era, when finance was declared a structured discipline, numerous researches have been undertaken to understand the markets and their various participants, with a special focus on investors. Their buying and selling decisions in the market have dominated the price movements and volatility of all the securities. Traditional theorists have based numerous models on the foundations of investors' rationality and information availability. Various models including the Arbitrage models of Modigliani & Miller, the Capital Asset Pricing Model of Sharpe, Lintner and Black and Markowitz portfolio model by Markowitz, have commonly assumed that investors are rational beings who have access to all essential information required to make investment decisions, which they incorporate when creating their investment portfolios. However, a contrasting viewpoint presented by some theorists suggests that investors may not always act rationally and could be influenced by emotions in their decision-making process.

A new contention suggests that investors do not necessarily analyze all the information at their disposal. They tend to select only the data they consider crucial for their decision-making process and disregard less significant details. The importance given to specific news or information is typically determined subjectively by the decision-maker, influenced by personal emotions and external factors.

Traditional finance emphasizes the significance of knowledge influencing financial asset valuations and the cautious approach of risk-averse investors relying on the balance between risk and return to make investment choices. Nevertheless, the continuous occurrence of financial crises and unaddressed anomalies in the stock market challenge the theories of market efficiency and investor rationality. In their influential 1979 publication, "Prospect Theory: An Evaluation of Decision Making in Risky Scenarios," Daniel Kahneman and Amos Tversky question the adequacy of expected utility theory in elucidating how decisions are made under conditions of uncertainty and propose a novel conceptual model called Prospect Theory. The seemingly contradictory nature of how people analyze risk in ambiguous circumstances has been clarified by their hypothesis, challenging the ideas of a perfect market and rational, consistently risk-averse investors, consequently giving rise to a new academic field called behavioral finance.

To understand why and how individuals make irrational, poor financial decisions, as well as the effects these decisions have on people's wealth, the performance of organizations, and the effectiveness of capital markets, behavioral finance merges the fields of psychology and economics. It claims that a variety of, inevitable behavioral biases have an impact on investment decision-making as well as that human brains use emotional filters and shortcuts when processing information. Thus, psychological factors are said to affect investment decision-making in behavioral finance. According to Pompian (2006), behavioral finance research focuses on a large body of information showing that human decision-making is ineffectual in a variety of economic decision-

making situations rather than a general theory of investing behavior [1]. Psychologists have made significant strides in elucidating the influences leading investors to diverge from making logical financial choices and the abrupt fluctuations in securities prices within the stock market, notwithstanding the conventional finance sector's resistance to embracing their perspective.

Investors have always exhibited these biases when active in the stock market. Therefore, studying an investor profile in the stock market will unfold several biases never seen before. This is the reason for numerous studies being conducted in the equity section of the stock market. But Tsoi (2004) in his study found that investors who hold a position in stock market equity as well as derivative segments are generally found to be more active in both the bearish as well as bullish markets [2].

LITERATURE REVIEW

Various literature has been found in earlier days supporting the rationality of investors. However, more recent studies conducted on investor psychology have revealed a number of different factors that affect an investor's rationality. Behavioral finance scholars assert that individuals are influenced by inherent psychological biases that impede their ability to make logical investment choices, thereby hindering market efficiency. Extensive research reveals the existence of market inefficiencies, evident through the continued presence of anomalies. Various factors such as cognitive and emotional biases, bounded rationality, intuitive reasoning, basic heuristics, limited information, and the dependence on historical performance, past experiences, and expectations contribute to irrational behavior and inefficiency. [3], [4], [5], [6], [7], [8], [9].

Denura, & Soekarno (2023) in their study found that Overconfidence, herding, and anchoring biases were found to be the main biases impacting an investor's decision-making in the cryptocurrency market of Indonesia. However, the authors also found that the financial literacy levels of investors have an impact on the biases impacting their decision-making in the market. Overconfidence, herding bias, disposition effect, anchoring, availability bias, and representativeness are the six most prevalent biases that have been the focus of research on the influence of behavioral biases on people's decisions regarding trading in securities [10].

Additionally, the majority of studies look at how a select few biases affect how individuals make decisions. For instance, studies on overconfidence show that this bias has a negative impact on financial choices. [11], [12], [13], [14], [15], [16], [17], [8], [18], [19], [20] [21]. According to Irshad et al. (2016) and Ikram (2016), representativeness bias has a favorable impact on individual investors' trading decisions [22] [23] .

However, according to other studies, representativeness bias negatively impacts how investors make decisions. [12], [13], [24], [25], [26], [27], [18]. Disposition effect studied by Dhar and Zhu (2006), Frazzini (2006), Barberis and Xiong 2009, Kuo and Chen (2012), Toma (2015), and Madaan and Singh (2019) gives contradictory results [28] [29] [30] [31] [32] [19]. Where some researches show no impact on trading choices, others show a negligible one. Studies on the effects of herding behavior also demonstrate that herding bias does not influence individual investors' decision-making processes, or only partially does so. [33], [34], [35], [36], [37], [19], [38]..

According to Shah et al (2018), anchoring bias adversely affects decision-making [18], whereas Madaan and Singh (2019) argue that this bias has no influence [19]. The impact of availability bias differs in various studies: Shah et al (2018) highlight a negative outcome [18], while Bakar and Yi (2016) identify a substantial effect [8]. Few studies have explored a range of behavioral factors, as noted by [39] [40] [18] [41]. Chandra and Kumar's research indicates that individual investment decisions are indeed impacted by behavioral biases. Their research emphasizes the notable impact of decision-making shortcuts such as regret aversion, anchoring and availability bias outweighing the aspects outlined in the prospect theory like loss aversion [39].

According to Kengatharan and Kengatharan's (2014) research, the investment choices of individual investors are impacted by four key behavioral factors: heuristics, herding, prospect, and market, each showing a significant influence [40]. Specifically, anchoring plays a prominent role, while stock selection has minor implications on investment decisions. Bakar and Yi's research highlights that overconfidence, conservatism, and availability bias significantly influence investors' decision-making processes, while herding behavior does not hold substantial significance [8].

According to Shefrin (2000), behavioral finance can assist practitioners in identifying and avoiding bias and inaccuracy in their judgements as well as in modifying and improving their overall investment strategy [42]. According to Tversky and Kahneman (1974), availability refers to the circumstance in which people determine an event's frequency or likelihood based on how easily examples may be remembered. According to Singh and Goyal (2016) and Jain et al (2021), individual investors can gain from becoming more conscious of the numerous human biases and the significant costs they place on their portfolios [43] [44]. There is evidence that indicates that the investor's experiences play a role in explaining this, with less experienced investors being more prone to extrapolation (i.e., representativeness) and more experienced investors being more prone to the gambler's fallacy, which is the erroneous belief that chance exists.

Rathi and Geetha (2023) claim Big Five Personality Traits and behavioral biases have a significant impact on public officials' investment decision-making, which may make such decision-making irrational. It was also found that investor education and setting up awareness programs play a major role in significantly controlling the impact of biases, in turn leading to rational decision-making [45].

Ahmad et al., (2022) discovered in their research on Pakistan Stock Exchange investors that biases influenced by recognition-based heuristics significantly impact investment choices, leading to both positive and negative outcomes. Their findings indicate that anomalies in fundamental and technical aspects play a mediating role in the relationship between these biases and investment strategies [46].

According to Sachdeva et al,. (2021), the research findings highlighted Investor Cognitive Psychology (ICP), Stock Characteristics (SC), and Market Information (MI), as the primary factors influencing herding behavior, with Socio-Economic Factors (SEF) being identified as the least influential factor in driving this behavior [47].

Yuniningsih and Santoso (2021) discovered that the variables of loss and regret aversion exhibited a substantial positive impact through direct and intervening examinations. Conversely, the financial literacy variables were deemed to have no significant effect when tested directly or indirectly[48]. Hesniati (2020) outlined that the primary findings indicate that certain behavioral factors, such as information asymmetry and availability bias, notably influence investment choices regarding gold instruments. In contrast, additional behavioral factors like anchoring, representative bias, and risk aversion were found to lack a significant effect on investment decisions [49].

Various research findings highlight the significant impact of behavioral biases on investors' decision-making processes. However, a considerable portion of these studies primarily focuses on the equity market. Therefore, there is a crucial and essential need to explore the influence of behavioral biases on derivative market investors in the Indian subcontinent.

METHODOLOGY:

Numerous scholars have argued that investors do not always act rationally, as various behavioral and psychological aspects influence their decision-making processes. This study has been undertaken to

examine the factors that influence individual investors when participating in the Indian Derivative market segment. A total of 250 samples were taken for this study where the respondents belonged to northern India. A cross-sectional survey design was adopted for the study where the questionnaire was floated to the investors and the samples with no presence in the derivative market were removed. This reduced the sample size to 200. Further study is conducted with this sample size.

For the identification and extraction of factors from the set of variables, factor analysis is employed. Factor analysis works on the assumption that several latent factors affect the observed scores on items or observations and thus the observations are then classified into a limited number of factors having the most impact on the dependent variables.

After the factors have been extracted, we find the total factor loadings of each variable or item. This factor loading is used to find how much impact the particular variable has on the factors. Those variables with a loading of less than 0.50 have been rejected while those above it have been accepted.

A standard score on a data item in a factor analysis can be stated as the weighted total of the scores for the common factor, the specific factor, and the error factor. Which is depicted numerically as:

$$S_{it} = L_{i1}F_{1t} + L_{i2}F_{2t} + \ldots\ldots L_{in}F_{nt} + L_{ii}S_{it} + L_{ie}E_{it}$$

Here,

S_{it} = Standard Score for Investor t on item i.

L_{i1} = Factor Loading on item i for common factor 1

L_{i2} = Factor Loading on item i for common factor 2

L_{in} = Factor Loading on item i for common factor n

L_{ii} = Factor Loading on item i for specific factor i

L_{ie} = Factor Loading on item i for error factor e

F_{1t} = Standard Score for Investor t on common factor 1

F_{2t} = Standard Score for Investor t on common factor 2

F_{nt} = Standard Score for Investor t on common factor n

F_{it} = Standard Score for Investor t on specific factor i

E_{it} = Standard Score for Investor t on error factor i

The initial matrix extracted from these factors identified is not used for analysis. This unrotated factor matrix is the correlation between the factors extracted and various variables in the study. These correlations are stated for each of the variables and factors. Hence, this is further rotated to understand the results carefully.

Results:

Table 1: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.627
Bartlett's Test of Sphericity	Approx. Chi-Square	415.632
	df	231
	Sig.	.000

The KMO metric is utilized to assess the appropriateness of data for conducting factor analysis. Factor analysis, a statistical technique, aims to identify latent variables or underlying factors that elucidate correlations among different variables. The KMO measure evaluates the interconnections among variables and determines their suitability for factor analysis.

The KMO statistic ranges from 0 to 1, with higher values indicating more suitable data for factor analysis. A KMO value below 0.5 is generally considered unacceptable, indicating that the variables are not sufficiently correlated to perform factor analysis reliably. In the table above, we find the KMO value to be 0.627. This indicates there exists enough correlation between the variables to run the factor analysis.

Bartlett's Test of Sphericity is another statistical test used in factor analysis. It determines whether the variables' correlation matrix differs significantly from an identity matrix, indicating that the variables are unrelated and therefore unsuitable for factor analysis. In the Table 1, the Bartlett's test indicates the chi-square value as 415.632. A higher value of chi-square indicates a greater level of discrepancy indicating the variables are not independent and therefore suitable for factor analysis. The degree of freedom indicates the number of independent observations used in the analysis.

The significance level in the above table is at 0.000, which indicates a very low p-value. A low p-value indicates the correlation between the variables under study.

Table 2: Descriptive Statistics

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N
Age	1.78	.848	100
Gender	1.44	.499	100
Level of Education	2.39	.875	100
Profession	2.29	1.104	100

Average Monthly Income	1.76	1.074	100
How active are you in the Derivatives segment of the market	1.68	.680	100
Other Investors' choice of stock has an impact on the type of security I choose.	3.04	1.154	100
The volume of security bought by me is impacted by the volume of stock bought by other investors.	3.04	1.154	100
My buying or selling decision in the derivative market is impacted by the decisions of other investors.	2.84	1.324	100
I react quickly to the changes in other investors' behavior than to the market signals.	2.92	.981	100
I fol2 the investor behaviour than the market signal while investing in the market.	3.12	1.217	100
I tend to believe in the market forecast by the Stock Analysts rather than study the market myself.	3.16	1.089	100
When I suffer loss in the market, I tend to be more risk-averse	3.04	1.286	100
I tend to hold on to the security if its value decreases, while sell off quickly the moment prices of security rise.	3.04	1.118	100
I treat all my investments in the market as a separate investment rather than as a whole	3.40	1.064	100
I ignore the connection between the various segments of the market and securities with each other	3.00	1.101	100
I carefully follow the price movement of the various derivative instruments in the market before investing.	3.48	1.030	100
Market Information for the stock as well as its Derivative is important in my decision-making process.	3.84	.972	100
l follow past trends of stocks and derivative markets before investing.	3.60	.943	100

I believe my knowledge of the Stock market helps in Derivative security selection.	3.20	.985	100
I believe my skills and knowledge of the market are enough to participate in the market	3.24	1.111	100
I am normally able to anticipate and predict the price movement in the derivative market.	3.00	.985	100

Rotated component matrices enhance the interpretability of factor analysis results by producing simpler and more meaningful factor structures. Varimax rotation aims to maximize the variance of the squared loadings within each component, leading to clearer and more distinct factor patterns that are easier to interpret.

Varimax rotation creates orthogonal (uncorrelated) factors, meaning that the factors are independent of each other. This simplifies the interpretation of factor loadings as each variable tends to load more heavily on one factor, reducing cross-loading and ambiguity in factor assignments.

PCA with Varimax rotation helps reduce the complexity of the factor structure by identifying the most important and independent factors that explain the maximum variance in the data. This allows

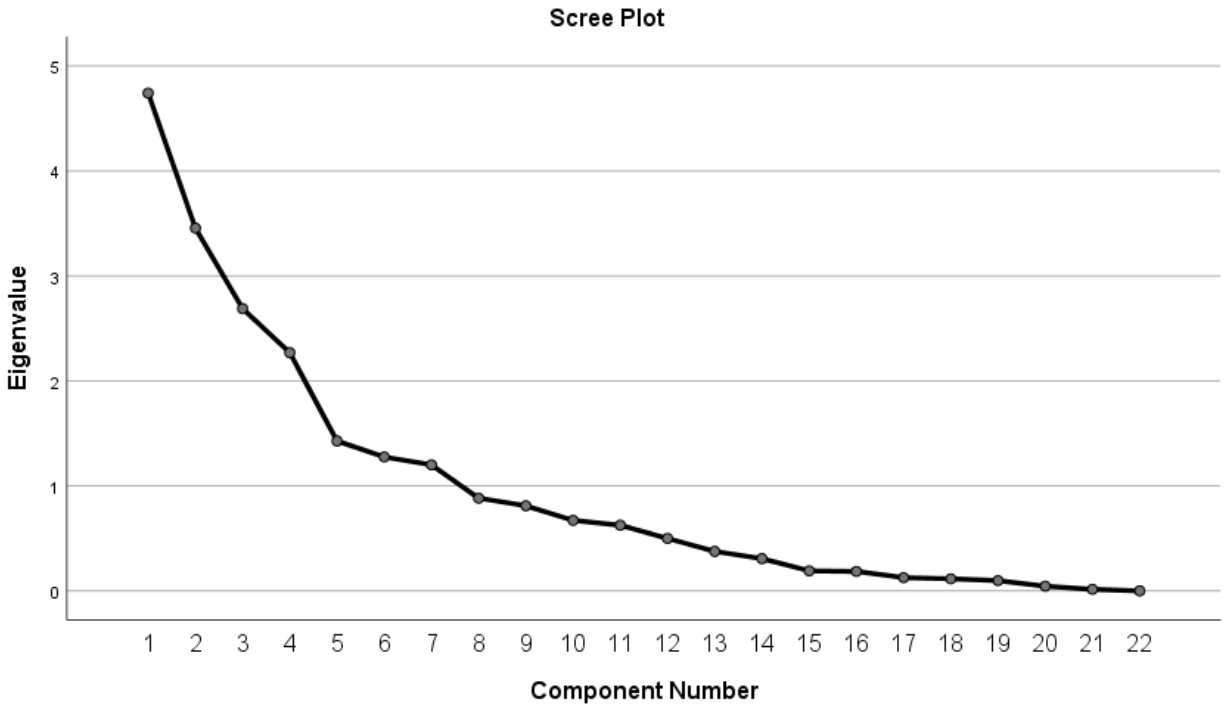

Figure 1: Scree Plot

researchers to focus on the key underlying dimensions or constructs influencing the observed variables Kaiser normalization is often applied during PCA to adjust the factor loadings by dividing them by the square root of the eigenvalue of each factor. This normalization procedure helps in improving the clarity and stability of factor loadings, making them more reliable indicators of variable associations with underlying factors. Varimax rotation and Kaiser normalization contribute to the statistical robustness of factor analysis results. By optimizing factor loadings and promoting factor independence, these techniques reduce the risk of overfitting and enhance the generalizability of the factor structure to new data. The combination of PCA with Varimax rotation and Kaiser normalization often leads to better model fit and convergence during factor analysis iterations. This ensures that the rotated component matrix adequately represents the underlying structure of the data and provides meaningful insights into the relationships between variables and factors.

Table 3: Rotated Component Matrix

Rotated Component Matrix[a]							
	Component						
	1	2	3	4	5	6	7
Age							
Gender					-.552		
Level of Education		-.772					

Profession		.548					
Average Monthly Income		.826					
How active are you in the Derivatives segment of the market?						.564	
Other Investors' choice of stock has an impact on the type of security I choose.			.954				
The volume of security bought by me is impacted by the volume of stock bought by other investors.			.954				
My buying or selling decision in the derivative market is impacted by the decisions of other investors.							.744
I react quickly to changes in other investors' behavior than to the market signals.				.916			
I follow the investor behavior than the market signal while investing in the market.				.697			
I tend to believe in the market forecast by the Stock Analysts than study the market myself.				.720			
When I suffer loss in the market, I tend to be more risk-averse		.515					
I tend to hold on to the security if its value decreases, while sell off quickly the moment prices of security rise.		.769					

I treat all my investments in the market as a separate investment rather than as a whole			.621				
I ignore the connection between the various segments of the market and securities with each other						-.806	
I carefully follow the price movement of the various derivative instruments in the market before investing.	.749						
Market Information for the stock as well as its Derivative is important in my decision-making process.	.887						
I follow past trends of stocks and derivative markets before investing.	.845						
I believe my knowledge of the Stock market helps in Derivative security selection.	.776						
I believe my skills and knowledge of the market are enough to participate in the market					.822		
I am normally able to anticipate and predict the price movement in the derivative market.					.809		
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]							
a. Rotation converged in 10 iterations.							

In Table 3 above, 7 major factors have been identified from the 24 variables. Factor 1 includes those behaviors that are impacted by the behaviors of other investors in the market. This shows that investors' decision-making is impacted by the influence of other investors.

Factor 2 describes the tendency of investors to ignore clear market signals and follow the steps of other investors. In this factor, the investor decision-making is based on their market responsiveness.

Factor 3 on the other hand collates the variables related to investor knowledge levels their belief about their knowledge as well as their current skills in the market.

Factor 4 captures the behavior of investors during times of uncertainty and market fluctuations and their risk aversion to these circumstances.

Factor 5 reflects the level of confidence investors have in their market knowledge and their abilities to predict the market.

Factor 6 counteracts two behaviors of investors. On one hand, investors tend to ignore the interconnection between various market segments and various securities traded. On the other hand, they tend to carefully follow the price movement of the particular security they are invested in.

Lastly, Factor 7 focuses on the reliance on market information and trends exhibited by the market. These investors follow past trends and historical data to glean the information present in the market and predict market behavior.

Based on the literature on criteria of selection of factors, only factors having at least 2 factor loadings can explain the factor's characteristics. Thus, for our study, factor 7 was dropped. Further study is done based on the remaining 6 factors.

Analyzing the various literature on biases, the characteristics of these factors can be named as follows:

1. **Factor 1**: Herd Behaviour/Social Influence
2. **Factor 2**: Investor Sentiment/Market Responsiveness
3. **Factor 3**: Overconfidence/Self-Perceived Expertise
4. **Factor 4**: Risk Aversion/Behaviour During Market Fluctuations
5. **Factor 5**: Market Segmentation/Information Processing Style
6. **Factor 6**: Information Reliance/Trend Following

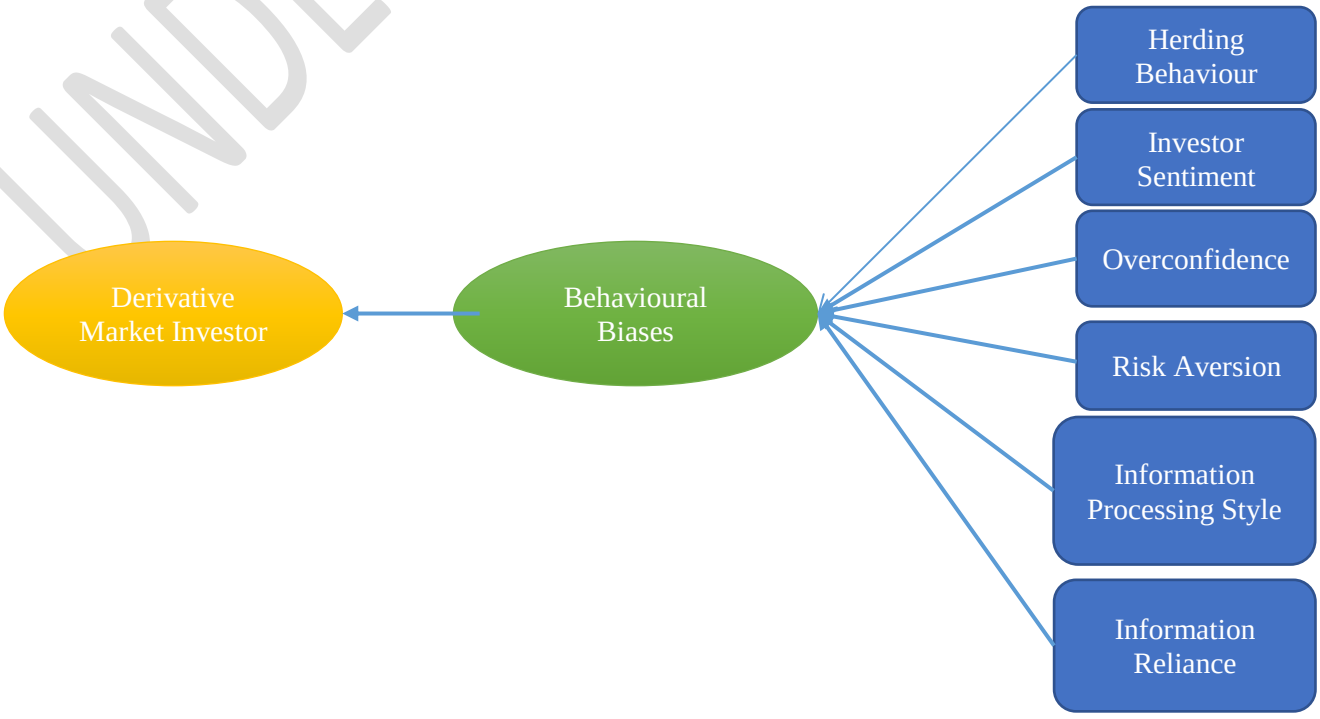

Figure 2: Research Framework

Table 4: Total Variance Explained

Total Variance Explained			
Component	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	3.390	15.409	15.409
2	2.922	13.282	28.691
3	2.846	12.935	41.626
4	2.539	11.541	53.167
5	2.366	10.753	63.919
6	1.587	7.213	71.132
7	1.408	6.402	77.534
Extraction Method: Principal Component Analysis.			

To find the reliability of the factors identified, a reliability test was run in SPSS. Cronbach's Alpha was computed for individual questionnaire factors to evaluate their internal consistency. This statistical measure, ranging from 0 to 1, signifies reliability – higher values reflect stronger reliability. Typically, a value exceeding 0.7 is deemed satisfactory, while values surpassing 0.8 are classified as good, and those surpassing 0.9 are excellent. The outcomes are concisely outlined in Table 5 below.

Table 5: Reliability Statistics

	Reliability Statistics		
Factors	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
F1	.962	.963	4
F2	.837	.819	4
F3	.809	.813	3
F4	.878	.883	3
F5	.888	.897	3
F6	.837	.839	2

Factor 1 (F1) exhibited impressive reliability, boasting a Cronbach's Alpha value of 0.962, which signifies an exceptionally strong internal coherence among the set of four items. This implies that these items consistently gauge the same fundamental concept.

Factor 2 (F2) demonstrated a Cronbach's Alpha coefficient of 0.837, suggesting a high level of reliability. The four components within this factor exhibit congruence in gauging the desired concept, instilling assurance in the factor's internal homogeneity.

Factor 3, denoted as F3, exhibited a Cronbach's Alpha value of 0.809, denoting a commendable level of reliability. The trio of components constituting this factor exhibited adequate coherence, establishing its dependability in assessing the associated construct.

Factor 4 (F4) exhibited a Cronbach's Alpha of 0.878, indicating strong reliability. The three components within this factor demonstrate consistency and dependability in assessing the targeted concept.

Factor 5 (F5) exhibited a high Cronbach's Alpha coefficient of 0.888, signifying excellent reliability. The three components within this factor consistently assess the identical fundamental concept, establishing the factor's strength.

The sixth factor (F6) obtained a Cronbach's Alpha value of 0.837, indicating a commendable level of reliability. Despite comprising solely two items, the elevated reliability score indicates that these items consistently gauge the targeted concept.

The examination of reliability reveals that every identified aspect displays strong internal coherence, as evidenced by Cronbach's Alpha scores significantly exceeding the adequate benchmark of 0.7. This affirms that the individual items within each aspect consistently gauge their intended constructs, establishing a sound basis for subsequent data analysis and interpretation. The elevated reliability metrics confirm the validity of the factor composition identified via exploratory factor analysis (EFA), reinforcing the reliability of the assessment instrument employed in this study.

CONCLUSION & SUGGESTIONS:

The study was conducted to identify the various behavioral factors that impact the decision-making of investors involved in the derivative segment of the exchange. The primary data was collected from the various derivative market investors and a structured questionnaire was adapted from the previous studies conducted. The study identified six major biases influencing the investment decision-making of the investors, namely, Herd Behaviour, Market Responsiveness, Overconfidence, Risk Aversion, Information processing, and information reliance. These factors have been supported by the major pieces of literature including

The findings of this study will be relevant to the retail players who invest in the derivative markets. There have also been found to be relevance to the managers and corporates who use derivative market to diversify their funds. Financial managers and investment advisors in the capacity of advisory services can also use this study to identify the biases they are impacted with and can work towards reducing their impact during decision-making. The managers may also use this study to identify the major risks associated with each of these biases and develop robust risk management systems and frameworks. Policymakers and regulating bodies can use the results of this study to better formulate policies leading to more transparency and disclosures of potential losses due to the influence of these biases in the derivative market.

Further study may be conducted on the impact of each of these variables on investor decisions. Apart from that, the factors contributing to the influence of each of these biases may further be explored.

Researchers may conduct a study on the other factors that have an adverse impact on behavioral biases. Lastly, biases may also be found and compared for various other segments of the market that are yet unexplored.

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