Biases in Capital Market Instrument Investing Decisions: A Study from India

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Abstract

This study examines the influence of different behavioral biases on the investment choices made by individual investors in the Indian capital market. The study utilizes a cross-sectional design, which entails gathering a substantial amount of data at a specific point in time. The study employed a survey methodology to collect data from a sample of 497 individual investors using purposive and snowball sampling. The data was collected using structural equation modeling (SEM), utilizing SPSS version 25 and AMOS version 26 as statistical software. This study characterizes individual investors as displaying irrational conduct. The study reveals a significant and positive association between representativeness, anchoring, and loss aversion biases and the investment decision-making process of individual investors in India. This study will enhance the current corpus of literature by examining the field of behavioral finance, which is gaining acknowledgment. Furthermore, few researchers have specifically examined these biases in developing countries, such as India.

JEL: B26, C51, D91, E71

Keywords: Behavioural Biases, Investment decision-making, SPSS, AMOS, Structural equation modeling

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INTRODUCTION

Traditional finance assumes in their theories that investors are rational, and the economic market hypothesis (EMH) conceptualized by Eugine Fama also proposed that markets are efficient. Each information in the market is reflected in the prices of the shares. But in reality, this does not seem to be happening. The behavior and decision-making of investors affect the stock market. It can be proved by the presence of bubbles and anomalies in the stock market. These bubbles and anomalies occur when the stock price exceeds the asset's intrinsic value.

On the other hand, some fundamentally strong stocks have stock prices less than their intrinsic value and vice versa. This overpricing and underpricing show that certain factors affect the investment decision-making of investors. It reveals that investors do not take their decisions rationally. Kahneman and Tversky also explained through their prospect theory in 1979 that investors do not make rational decisions. Different factors affect individual investors' decision making and therefore, this study was conducted to measure the impact of behavioral biases on investment decision-making.

A few researchers have already conducted research to measure psychological biases that impact investment behavior (Chira et al., 2008; Ogunlusi and Obademi, 2019). However, they considered only three to four biases in their studies. Parveen et al. (2021) and Ahmad and Shah (2020) suggested in their study that further research should be done considering more biases. Therefore, this study has identified the impact of eight biases on investment decision-making: overconfidence, representativeness, herding, availability, anchoring, mental accounting, loss aversion, and disposition biases.

Most behavioral finance studies have been conducted in developed nations, supported by Sharma and Kumar (2020) and Quaicoe and Eleke-Aboagye (2021), and the area of developing nations is unexplored (Ahmad et al., 2020). Unlike mutual fund investors, this study considered only those directly investing in the stock market. Therefore, this study analyzed the decision-making of Indian investors investing in capital market instruments. According to the BSE report, investors from three states, namely, Maharashtra, Gujarat, and Uttar Pradesh, were selected for research since these three states have the highest number of retail investors.

LITERATURE REVIEW AND HYPOTHESIS FRAMEWORK

Overconfidence Bias

Overconfidence bias was found to be the most prominent bias that exists in individual behavior. Prosad *et al.* (2017) found that overconfident bias exists in every sector of the economy. So, it is not industry-specific. Emerging countries like Pakistan, Tunisia, and Estonia are affected by overconfidence bias due to their weaker economic policies, inefficient markets, corruption, and high volatility. Developed countries like the USA and France are also affected by this bias due to the impact of the global economic crisis. Tekce and Yilmaz (2015) found that developing countries are more affected by overconfidence bias than developed countries because of the lower rate of financial sophistication in developing nations. Overconfident investors trade excessively (Chuang and Susmel, 2011; Odean, 1999; Odean and Barber, 2000; Odean and Barber, 2001; Glaser and Weber, 2007), and their turnover rate is high.

Overconfidence bias and investment decision-making

Overconfident investors exaggerate their private information and, thus, the anticipated trading gains. They may trade even when expected net losses are anticipated (Odean and Barber, 2001). Odean (1999) claimed that the equities a person sells outperform the ones they purchase. It indicates that overconfident investors fare poorly in the stock market. In a bullish market, individual investors become more overconfident (Chuang and Susmel, 2011). Overconfident investors overestimate their private information and actively trade. Odean and Barber (2000) found that the investors who trade the most are hurt the most. It shows that due to overconfidence, investors sometimes suffer losses.

On the contrary, Bouteska and Regaieg (2018) concluded in their study that overconfident investors in the industrial sector can benefit shareholders by increasing trade returns and profitability and lowering risk. It happens because the competition in the industrial sector is rougher than in the service sector. Investors are found to be more loyal or faithful in the industrial sector. In addition, U.S. companies benefit if the investors are less pessimistic and less loss-averse. Gavrilakis and Floros (2021) also revealed that strong overconfidence improves portfolio construction and performance satisfaction levels. Therefore, the following hypothesis is created to check the impact of overconfidence bias on investment decision-making-

H1: Overconfidence bias has a significant positive influence on investment decision-making.

Disposition Bias

Shefrin and Statman (1985) coined the term disposition effect to describe the tendency of investors to sell winners too early and ride losers too long. Kahneman and Tversky (1979) established a prospect theory in which they discovered that investors obey disposition bias in uncertain situations. Since decision-makers adhere to the S-shaped valuation function, which is concave in the gain zone and convex in the loss region, this demonstrates that investors become risk-averse during gain and risk-seeking during periods of loss. Shifrin and Statman (1985) examined the impact of four factors on disposition bias: tax consideration, regret aversion, mental accounting, and self-control.

Disposition bias and investment decision-making

Significant positive market returns (up to the past month) motivate them to sell, and recent negative market returns (up to the past week) reduce their choice to sell the stock. Odean (1999) also supported this by stating that investors sell stocks that have performed well in recent weeks. Prosad *et al.* (2015) found that middle-aged investors are affected by disposition bias as they increase trading when they get past success in their returns. Therefore, the hypothesis is created to check the impact of disposition bias on investment decision-making-

H2: Disposition bias has a significant positive influence on investment decision-making.

Mental Accounting Bias

Mental accounting is the mental operations individual investors use to organize, evaluate, and keep track of financial activities. In this, the individuals create different accounts for their different financial activities. Every account is managed and assessed differently. Different budgets are allocated to different accounts. Rajgopal and Rha (2009) examined the way investors perceive time. They found that investors also make mental accounts for their time. They allot time to different mental accounts to balance their work and non-work activities. Kahneman and Tversky (1979) also supported this bias in prospect theory. Mental accounting violates the principle of fungibility (Thaler, 1999).

Mental accounting and Investment decision-making

Research by Thaler and Johnson (1985) showed that investors are reluctant to close their losing mental account and open a new mental account of similar value. Mascarenes and Yan (2017) found that every investor can take risks differently. Each investor has a mental account of risk and return. Investors consider these two accounts while making investment decisions. The following hypothesis can measure the effect of mental accounting on the investment decision-making of investors-

H3: Mental Accounting bias has a significant positive influence on investment decision-making.

Herding Bias

When the investors imitate the behavior of other investors, they are affected by herding bias. Investors follow the behavior of others when they have limited information or think others have more information and knowledge. At times of uncertainty, identifying the stock's actual value becomes difficult. Therefore, investors are more affected by behavioral biases. It was found that volatility is positively related to herding bias. Herding bias makes the market more volatile (P.H. and Uchil, 2020). at the time of a bullish and bearish market, the effect of this bias is found to be prominent (Kim and Nofsinger, 2007).

Herding bias and Investment decision-making

Singh (2018), Soni and Desai (2019), Qasim et al. (2019), Raut et al. (2018), Quaicoe and Eleke-Aboagye (2021), and Jain et al. (2019) discovered that herding bias significantly affects investment behavior. This bias also affects professional investors in addition to individual investors. Gavrilakis and Floros (2021) analyzed the portfolio development of professionals and discovered that herding bias had a negative effect on portfolio construction in Greece. Using the following hypothesis, we evaluate the impact of herding bias on investment decision-making:

H4: Herding bias has a significant positive influence on investment decision-making.

Loss aversion bias

The concept of loss aversion arose with the development of the prospect theory by Kahneman and Tversky (1979). In loss aversion, the pain of loss exceeds the pleasure of achieving benefits. It is defined by Kahneman and Tversky (1984) as the disutility of giving up an object that is more significant than its utility. Loss aversion makes the investor risk-averse. They refrain from investing out of fear of losing.

Loss aversion bias and Investment decision making

Shafqat and Malik (2021) investigated the behavior of 384 investors on the Pakistan stock exchange and discovered that loss aversion has a negative effect on trading frequency. Singla and Hiray (2019) and Prosad et al. (2015) found that this prejudice is prevalent among women and older people. People avoid hazardous investments because women prefer to invest in fixed-income instruments and because their age increases. Women are more risk-sensitive than males. It influences every element of their decision-making, including their choice of job, investment decisions, and the things they choose to purchase (Eckel and Grossman, 2008).

H5: Loss aversion bias has a significant positive influence on investment decision-making.

Availability bias

This bias was introduced by Kahneman and Tversky in 1973. When the decision is taken based on how easily the instance comes into mind. Availability bias is a part of heuristics. Heuristics are the shortcuts we use to reduce multiple calculations. Availability-biased investors make a decision considering available information and ignore unavailable information. Availability bias is used to assess the frequency of an event. Kahneman and Tversky (1974) and Meng (2017) identified four factors affecting availability bias: irretrievability, imaginability, illusory correlation, and the effectiveness of the search set. The first factor is irretrievability, in which an individual thinks that the frequency of a specific event is higher when similar or related past events are easily retrievable. The second factor, imaginability, is a heuristic when an individual needs to assess a situation based on given rules instead of their memory. The third factor, illusory correlation, is a phenomenon in which two events are perceived to be related, but in reality, they are unrelated. The last factor, the effectiveness of the search set, is a phenomenon in which the occurrence of certain instances is linked with the effectiveness of the search. Therefore, the following hypothesis is created-

H6: Availability bias has a significant influence on investment decision-making.

Anchoring Bias

Anchoring originates in the 1974 publication "Judgement under Uncertainty: Heuristics and Biases" by Kahneman and Tversky. They demonstrated anchoring bias through various tests and discovered that people assign a higher weight to the initial information (Anchor). According to Tversky and Kahneman (1974), anchoring bias happens when people make decisions based on too much pre-existing information or the first information they find (anchor).

Anchoring bias and investment decision-making

According to Ducles (2015), if the previous day's closing price is higher than the previous day's opening price, indicating that the previous day was an upward-moving day, the following day's prognosis is upward movements, leading to more significant investments that day. When the chart has more conspicuous highs than lows, investors purchase more and sell less, according to Mussweiler and Schneller (2004). According to George and Hang (2004), the 52-week high and low are used as the anchor for predicting future returns, although this method is only effective in the short term and not the long term. According to Grinblatt and Keloharaju (2001), investors are more inclined to sell and more likely to buy stocks whose prices are close to historical highs. Therefore, the following hypothesis is created-

H7: Anchoring bias has a significant influence on investment decision-making.

Representative Bias

The representativeness bias is the tendency for individuals to make decisions based on their preconceived views, prior knowledge, or personal experiences. When representativeness bias exists, individuals rely on a few observations to obtain information about their environment and disregard other data when making decisions (Baker & Nofsinger, 2002; Ritter, 2003; Shefrin, 2000). Due to representativeness bias, investors overreact while processing and evaluating information (Kahneman & Riepe, 1998). According to the studies of Franses (2007) and Marsden et al. (2008), representativeness bias can lead to overreacting behavior, which is reflected in stock prices.

Representativeness bias and investment decision-making

Representational bias can lead to erroneous investment judgments. One of the misconceptions that investors have about the capital market, according to Chen et al. (2007), is that a company with strong features, such as high product quality, dependable managers, and significant growth, is a solid investment. The representativeness bias also causes investors to conclude that a stock's past performance is the best predictor of its future performance (Frensidy, 2016). Investors believe that a company's past performance indicates its future performance (Boussaidi,2013). In addition, people are forced to rely on recent past experiences when making investment decisions due to a lack of information and awareness of data-analysis tools and procedures, which are crucial for evaluating alternative investment options. Consequently, the following hypothesis is developed-
H8: Representativeness bias has a significant influence on investment decision-making.

RESEARCH METHOD

Target Population

Individual investors in the Indian stock market who invest in capital market instruments are the focus of this study. Although the investors analyzed in this study were from India, the findings apply to investors from other developing nations.

Sampling and Data collection

The primary purpose of this study is to investigate how behavioral biases influence the decisions and performance of individual Indian Stock Market participants. Seven hundred questionnaires were sent to individual Indian investors already trading on the Bombay Stock Exchange to accomplish the research objective. Individual investors returned 550 questionnaires, but 497 were fully completed and analyzed, representing a response rate of 71%. This sample size is sufficient for meeting all statistical standards. This was also corroborated by a study of research conducted on similar themes in different locations, including those of Bhatia et al. (2021), Raut et al. (2018), Mouna and Jarboui (2015), Waweru et al. (2008), and others, in which the sample size ranged from 250 to 400. According to Hair et al. (1998), for statistical data analysis techniques to produce dependable results in quantitative research, data from at least 100 respondents must be gathered. Snowball and convenient purposive sampling were employed to acquire data for this investigation. Because for random sampling, data from the entire population is necessary, a random sample technique was not applied (Sekaran and Bougie, 2016). The Indian economy is a developing country; as a result, standard data formats are unavailable, so the researchers employ a non-random sampling technique.

There are various ways to collect data, including structured interviews, unstructured interviews, semi-structured interviews, observation, and group discussions. The self-reported questionnaire, one of the most prevalent quantitative research methods, was chosen as the data collection method for this study because it was more time and cost-efficient than other methods, such as interviews, videoconferencing, and brainstorming (Bryman and Bell, 2007). Individual investors were naturally inclined to avoid personal interviews and provide adequate time to researchers. In this case, questionnaires were deemed the most effective technique of data collecting because respondents could fill them out whenever they had the time, and the researchers could not have a direct influence.

Research Design

This study used Exploratory and Cross-Sectional Research design. Exploratory research design

Instrumentation of Data Collection

The survey is divided into three sections: Section A: Population characteristics. It includes the age, gender, income, employment, education, trading experience, marital status, and occupation sector of individual investors. Section B: Focuses on psychological biases. On a five-point Likert scale, 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = highly agree. The questions pertain to psychological biases. Section C: Investment decision-making. The investors' investment decision-making was examined using a five-point Likert scale.

RESULTS

The questionnaire-collected data were analyzed using SPSS version 25.0 and Amos version 26.0. First, a pilot test was conducted to determine the instrument's validity and reliability; secondly, statistical approaches, including Cronbach's alpha test, descriptive statistics, correlation analysis, factor analysis, and structural equation modeling, were employed to meet the research objectives. The majority of previous studies (Lebdaoui et al. (2021); Suresh (2021); Jain et al. (2021); Singla and Hiray(2019); Ainia and Lutfi (2019); Subramaniam and Velnampy (2017)) analyzed the behavior of investors using structural equation modeling (SEM).

Sample Demographics

The demographic features of the 497 survey respondents are shown in Table I.

Table 4.1: Demographic Descriptive of Respondents

Profile	Group	Frequency	%
Gender	Male	402	80.89
	Female	95	19.11
Age	18- 25	53	10.66
	26-35	311	62.58
	36-45	106	21.33
	46-55	20	4.02

		Above 55		7		1.41
Income (Monthly)		Below 20000		12		2.41
		20000-50000		116		23.34
		50001-100000		280		56.34
		100001-200000		80		16.10
		200001-500000		7		1.41
		Above 500000		2		0.40
Education		10+2		6		1.21
		Undergraduate		137		27.57
		Post Graduate		237		47.69
		Doctoral		3		0.60
		Professional qualification		114		22.94
Marital Status		Single		242		48.69
		Married		255		51.31
Primary Source of Regular Income		Full Employment		303		60.97
		Retirement Benefits		2		0.40
		Self - Employment		165		33.20
		Your own Company		5		1.01
		Other		22		4.43
Investment Experience(in Years)		Less than two years		128		25.75
		2-5 Years		284		57.14
		>5-10 Years		74		14.89
		>10 Years		11		2.21
Occupation Sector		Financial Sector		189		38.03
		Non-Financial Sector		308		61.97

Common Method Bias

Since the present study utilized cross-sectional data, CMB was evaluated using Harman's single-factor test and principal component analysis in SPSS. The analysis reveals twenty factors with eigenvalues greater than 1, with the first factor explaining less than fifty percent of the total variance (15.52%). It verifies that there is no risk of Common method bias (CMB) influencing the

Testing Normality Assumption

Many authors recommended that before analyzing the data, the assumption of normality of data should be tested (Lu *et al.*, 2005; Kuo *et al.*, 2009). The data collected was normal since skewness < ±1 and kurtosis < ±3 are in the specified range (Hair *et al.,* 2010).

Factor Analysis

Factor analysis examines measuring items for behavioral biases and investing behavior. The items are extracted using principal component analysis (PCA) with Varimax rotation. The rotational pattern matrix offers nine-factor behavioral biases and investment behavior solutions. Exploratory factor analysis revealed 0.843 Kaiser–Meyer–Olkin sample adequacy. Nine behavioral biases and investment behavior components with eigenvalues >1 explain 56.08 percent of the variation. They rotated factor loadings of each item in Table 4.2 greater than 0.7 (Hair et al., 2010).

Table 4.2: Statements of measured items and factor loadings

Items	Statements	Factor Loading
OC1	You feel that your stock market expertise and talents will allow you to outperform the market.	.794
OC2	You know the optimal times to enter and exit the market with your investments.	.767
OC3	You are more confident in your investment opinion than your coworkers or friends.	.807
OC4	You engage in trading more regularly than others.	.758
OC5	You are always enthusiastic regarding the future profits of your assets.	.780
OC6	You are an expert on the many sorts of investing.	.812
REP1	All of your investment decisions are determined by a trend study of some of your similar investments from the past.	.846
REP2	You like to invest solely in well-known companies.	.818
REP3	You maintain the same position even if your best-researched stock does not perform as expected.	.802
REP4	If other stocks of a company are performing well and the company is offering new shares, you will purchase those shares.	.812
REP5	You invest in "Hot" equities and avoid those that have underperformed in the past.	.845
HRD1	The stock choices of other investors influence your investment decisions.	.838
HRD2	You typically respond rapidly to changes in the decisions of other investors and mimic their stock market movements.	.802
HRD3	You monitor social blogs/forums before buying/selling securities.	.821
HRD4	When you lose money on an investment, your disappointment is lessened if other investors suffer the same loss.	.811
HRD5	You do not make any investing decisions independently.	.842
AVL1	When evaluating the historical success of an investment, you place greater emphasis on its recent performance	.792
AVL2	The primary source of information for your financial decisions is advertisements.	.805
AVL3	You like purchasing equities on days when the value of the index rises.	.796
AVL4	You favor investing in stocks that well-known analysts have assessed.	.798
AVL5	You prefer to purchase local stocks over international ones.	.792
AVL6	You like to sell equities on days when the index falls in value.	.807
ANC1	Typically, you invest in stocks that have declined significantly from their previous closing price or all-time high.	.827
ANC2	In trading, you use stock purchase price as a reference point.	.795
ANC3	You rely on your prior market experiences while making your next investment.	.806
ANC4	Based on recent stock prices, you predict future changes in the stock market.	.816
ANC5	You determine in advance the desired price for buying and selling the security.	.815
MTA1	You assess income and capital appreciation returns separately.	.808
MTA2	You divide your investments into recreation, children's education, etc.	.777
MTA3	You dispose of lost investments in your portfolios.	.804
MTA4	You tend to treat each element/account in your investment portfolio independently.	.787
MTA5	You ignore the connection between different investment possibilities	.779
MTA6	You own shares of companies A and B. Company 'A' is your dream company, whereas Company 'B' piques your curiosity due to its incredibly promising profits. Suppose the share prices of both of these firms decline, but the share prices of 'A' decline more than those of 'B,' and you must sell shares of one of the companies. Will you sell the company's Class A shares?	.817
LA1	You refrain from investing when you anticipate a loss.	.823
LA2	a loss of 1000 rupees is more painful than a gain of 1000 rupees	.753
LA3	When presented with a certain profit, you are risk-averse.	.770
LA4	You are a risk-taker when faced with certain losses.	.782
LA5	You resist selling shares that have depreciated and are eager to sell ones that have appreciated.	.772
LA6	You routinely evaluate the success of your stock portfolio.	.791
LA7	You postpone making choices for fear of suffering losses.	.820
DP1	You are slow to react to good or bad news and tend to sell lucrative stocks too early and lose stocks too late.	.850
DP2	You are frequently unwilling to accept losses.	.815

DP3	You sell successful stocks out of concern that the price may decline again.	.850
IB1	You base your stock-buying decisions on historical data, such as the company's previous returns.	.852
IB2	You base your stock purchase selections on the company's fundamentals (dividend pay-out, cash flows, and earnings growth).	.840
IB3	Typically, you receive the anticipated return on your investment selection.	.849
IB4	Most of the time, your investing decisions complement your investment goals.	.857

Reliability Assessment

The approach of Cronbach's coefficient is used to assess the dependability of the variables. Table A1 displays a strong association between all items within each component. Each construct's Cronbach's exceeds the suggested value of 0.7, indicating that everything inside each construct is closely connected (Hair et al., 2006).

Measurement model

A measurement model explains the relationship between measured and latent variables in confirmatory factor analysis. The measurement model is shown in Exhibit 4.1. Indices for assessing model fit are computed to evaluate the adequacy of the measurement model. The values of the indices presented in Table 4.4 indicate that the entire index values fall within the predetermined acceptable ranges. The values of CMIN/df (998), CFI (0.956), GFI (0.885), AGFI (0.87), TLI (0.952), IFI (0.956), NFI (0.887), RMSEA (0.034), and RMR (0.024) fall within the approved range, suggesting that the model fits well. Hence, it can be deduced from the confirmatory factor analysis results that the model exhibits a favorable fit and is appropriate for subsequent study.

Convergent validity

The convergent validity is attained if the subsequent conditions are met:
- The C.R. should exceed the AVE.
- AVE must be more than 0.5 (Hair et al., 2012).

Table 4.4 presents the statistics for all nine dimensions. In the present study, both prerequisites mentioned above are met, providing solid evidence of convergent validity.

Discriminant validity

A measure's discriminant validity assures it does not correlate strongly with another. In this study, the discriminant validity was evaluated using Fornel and Larcker's (1971) technique. It was accomplished by comparing the square root of each AVE from Table 4.3 to the correlation coefficient from Table A2 for each construct in the relevant rows and columns.

Table 4.3: Validity of Different Constructs

Constructs	CR	AVE	SQRT (AVE)
Overconfidence	0.98	0.56	0.75
Representativeness	0.98	0.66	0.81
Herding	0.98	0.61	0.78
Availability	0.98	0.59	0.77

Anchoring	0.98	0.61	0.78
Mental Accounting	0.98	0.59	0.77
Loss Aversion	0.99	0.59	0.77
Disposition	0.94	0.59	0.77
Investment decision-making	0.97	0.68	0.83

Structural Model

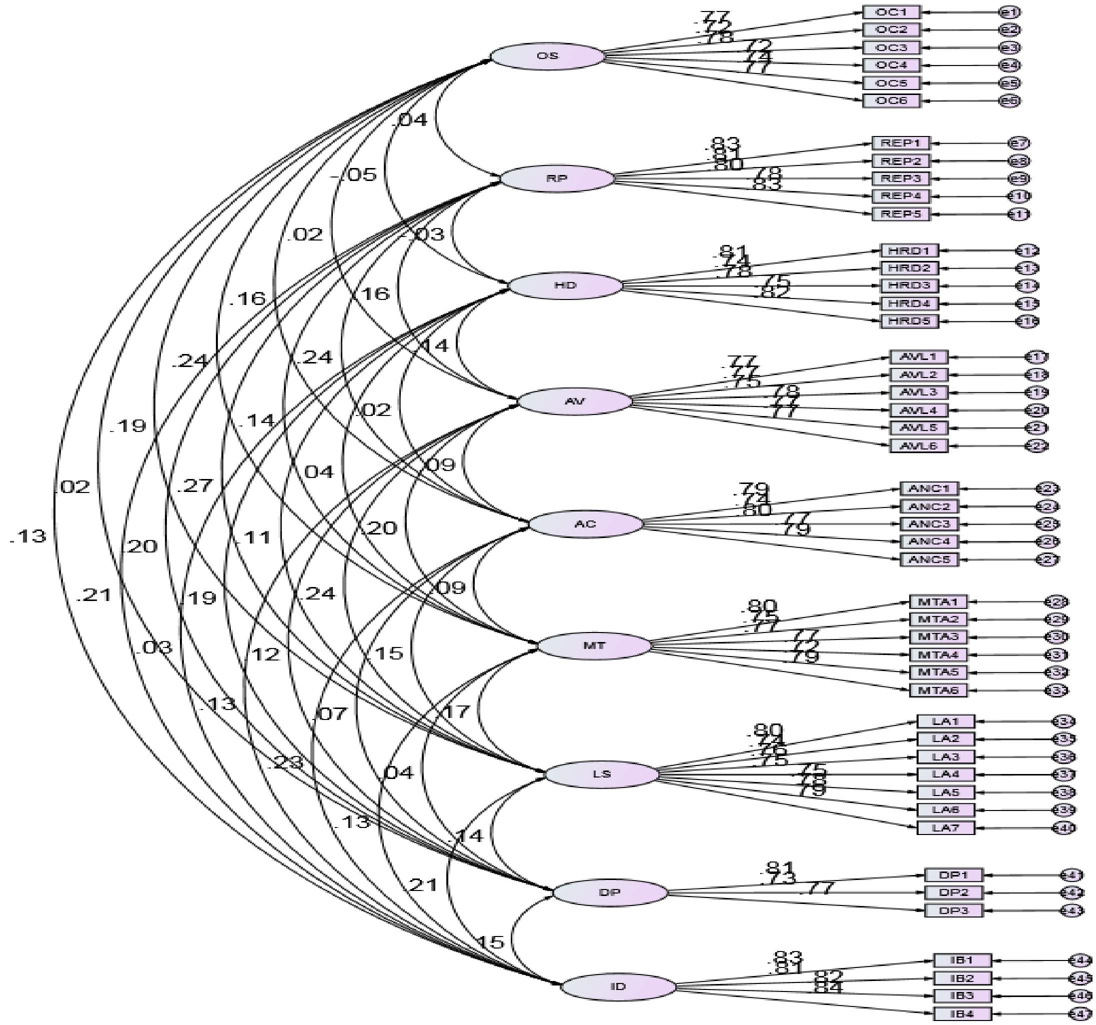
To evaluate the postulated theoretical association between behavioral biases and IDM, the study used structural equation modeling with IBM AMOS Version 26. Model fit indices for the structural model are χ^2 = 1562.39, df = 998, 2/df = 1.566, CFI = 0.956, GFI = 0.885, TLI = 0.952, IFI = 0.956, NFI = 0.887, AGFI = 0.870, RMSEA = 0.034, and RMR = 0.024, validating the structural model's fitness (Table 4.4).

Table 4.4: Model fit indices for structural model

Fit indices model	Recommended level of fit indices	Measurement Model	Structural Model
χ^2		1562.395	1562.39
Df		998	998
χ^2/df	<3 (Kline, 1998)	1.566	1.566
CFI	>0.90 (Hu and Bentler, 1999)	0.956	0.956
GFI	>0.90 (Hair et al.,2010) and > 0.80(Baumgartner and Homburg, 1996; Doll et al.,1994)	0.885	0.885
TLI	>0.90 (Hu and Bentler, 1999)	0.952	0.952
IFI	>0.90 (Bollen, 1990)	0.956	0.956
NFI	>0.90 (Bentler and Bonnet, 1980)	0.887	0.887
AGFI	>0.90 (Hooper et al.,2008) > 0.80(Baumgartner and Homburg, 1996; Doll et al.,1994)	0.87	0.87
RMSEA	<0.10 (Wan, 2002; Schermelleh-Engle et al., 2003)	0.034	0.034
RMR	<0.10 (Hair et al.,2010)	0.024	0.024

Note: This table shows the fit indices for measurement and structural model. Parentheses show the recommended indices suggested by different authors.

Exhibit 4.1: Measurement Model



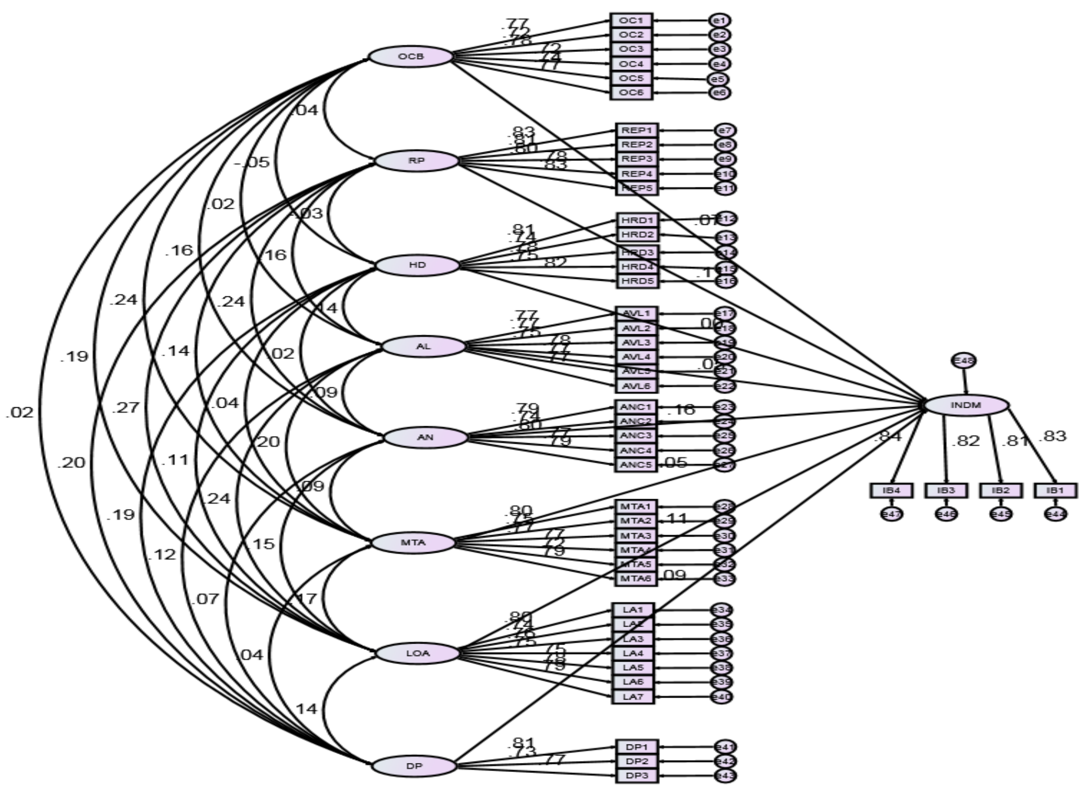
Path Analysis

Eight exogenous variables (O.C., REP, HRD, AVL, ANC, MTA, LA, and DSP) and one endogenous variable are included in the model (IB). As seen in Table 4.5, the data support three of the eight hypotheses. The findings suggest that representativeness (REP), anchoring (ANC), and loss aversion (L.A.) have a substantial positive relation with investment decision-making (I.B.) at the 0.05 level of significance. The supported hypotheses are, therefore, H5, H7, and H8. The unsupported hypotheses are, therefore, H1, H2, H3, H4, and H6. The influence of overconfidence, herding, availability, mental accounting, and disposition biases on investing decision-making is insignificant.

Table 4.5: Result of Hypothesis tests

Proposed rotation path	Hypothesis	Path coefficient	P-value	Hypothesis supported
IDM <-- OC	H1	0.079	0.19	NO
IDM <-- DSP	H2	0.11	0.094	NO
IDM <-- MTA	H3	0.062	0.306	NO
IDM <-- HRD	H4	0	0.997	NO
IDM <-- LA	H5	0.129	0.039	YES
IDM <-- AVL	H6	0.066	0.301	NO
IDM <-- ANC	H7	0.19	0.002	YES
IDM <-- REP	H8	0.116	0.039	YES

Exhibit 4.2 Structural Model



DISCUSSION AND CONCLUSIONS

This study explores the link between behavioral biases and the investment decisions of individual Indian investors. Given a country's diverse population of individual investors, retail investors play an essential role in a rising economy. Three behavioral biases are highly associated with the investment decisions of Indian stock investors, according to the investigation. In a broader sense, the results indicate that representativeness has a strong and positive relationship with the investment decisions of individual investors in India. These findings are in line with those of Seth and Kumar (2020), Irshad et al. (2016), Rehan and Umer (2017), Subramaniam and Velnampy (2017), Hunguru et al. (2020), and Cuandra and Tan (2021), but contradict those of Aigbovo and

Ilaboya (2001). (2019). Based on these data, an important conclusion is that Indian retail investors with a representative bias base their investing decisions on preoccupied knowledge and prior experience. The performance of equities in the past influenced these investors. They believe that a company's history of exceptional achievement indicates the overall performance it will continue to generate in the future (Boussaidi, 2013).

According to the results, anchoring bias has a significantly positive relation with the investment decision-making of Indian retail investors. The Indian investors make decisions based on the first information they collect or the only information available. Indian investors give more weightage to the prices at which the stock is bought. They generally sell the stock if they notice an increase in the prices and hold or buy more if they observe a decrease in stock prices. Investors are more inclined to sell and more likely to buy stocks whose prices are close to historical highs said Grinblatt and Keloharaju (2001).

The findings also show that loss aversion bias has a statistically significant and positive relation with the investment decision-making of Indian individual investors. The Indian investors are likely to be risk-averse and less overconfident. Since loss aversion is negatively correlated with overconfidence bias, Indian investors invest less due to the fear of loss or in fixed-income securities. Myopic loss aversion (Benartzi and Thaler, 1995), the combination of high rebalancing frequency with loss aversion, is also found in Indian investors. It means Indian investors, frequently check their investment performance and trade regularly. Langer and Weber (2008) found that myopic loss aversion is significantly and positively correlated with investors' equity investments. It shows that Indian investors who evaluate and rebalance their portfolios frequently invest less in equities.

In future studies, the sample size can be raised as there is an urgent need to undertake similar empirical investigations on larger data sets. Investigating several moderating variables to gain a complete picture would be prudent. Future research could also investigate the impact of demographic (age, gender, income, occupation, education, marital status, and investment experience) and social (friends, family, and media) variables on behavioral biases and investment decision-making. Future research should compare the investment patterns of developing and industrialized nations. This research has also been limited to the eight behavioral biases influencing investors' decision-making. The study's scope can be expanded by collecting other behavioral biases.

Theoretical Implications

This study's findings support prospect theory. Prospect theory is an essential theoretical breakthrough developed to explain conduct that deviates consistently and systematically from expected utility theory. According to this idea, investors become risk-takers in the event of losses and risk-averse in the event of winnings (Kahneman and Tversky, 1979). According to the findings of this study, loss aversion is highly associated with investing decisions. It demonstrates the validity of the prospect theory with the conduct of Indian Stock Exchange investors. Additionally, these findings demonstrate the existence of prospect theory in investment behavior. This study, however, refutes the house money effect, which proposes that investors become risk-averse during losses and risk-seeking during wins (Thaler and Johnson, 1990).

This research supports the heuristic theory as well. Heuristics are the mental shortcuts that enable people to solve issues and make decisions efficiently and swiftly. This theory was developed by Kahneman and Tversky in 1974, and it explored several biases, including representativeness, availability, adjustment, and anchoring. The findings of this study indicate that representativeness and anchoring have a substantial impact on the decision-making of Indian retail investors. Consequently, heuristic theory is supported by the present investigation.

Practical Implications

If investors exhibit behavioral biases, the Indian stock market is affected. Therefore, it is an enormous obligation for all parties to exercise sufficient care and prudence while making financial decisions. The study's findings have substantial managerial implications for stakeholders, including individual investors, fund managers, policymakers, and the academic community.

Our research assists individual investors in recognizing the influence of behavioral biases such as representativeness, anchoring, and loss aversion on their investment decision-making, enhancing the rationality that leads to market efficiency. The investors should conduct a post-investment review of each investment to recognize past behavioral errors and avoid repeating them.

Before building their portfolios, it is proposed that fund managers should attempt to detect behavioral biases in their clients. In pursuit of profitability, they must also exercise extreme caution when employing volatility-based trading tactics. To avoid a "wealth loss" situation for investors and themselves, it is essential that they "de-bias" themselves by applying the appropriate knowledge and making reasonable investing decisions. To reduce the influence of these biases on the stock markets, policymakers such as SEBI should design solutions based on behavioral finance principles. It can organize workshops to educate investors on security analysis so they to make sensible decisions. Academicians can develop new behavioral models that illustrate strategies for addressing behavioral biases during decision-making.

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APPENDIX

Table A1: Reliability assessment of research Instruments

Item	Cronbach's α	Inter-item correlation
OC	.886	.45-.62
REP	.904	.57-.69
HRD	.886	.52-.67
AVL	.895	.53-.64
ANC	.885	.51-.66
MTA	.895	.50-.65
LA	.909	.50-.65
DSP	.813	.56-.62
IDM	.895	.64-.71

Note: O.C., overconfidence; REP, representativeness; HRD, herding; AVL, availability; ANC, anchoring; MTA, mental accounting; L.A., loss aversion; DSP, disposition bias; IDM investment decision making. Cronbach's α coefficient > 0.7 indicates reliable data.

Table A2: Correlation Matrix indicating Discriminant validity

	DSP	LA	MA	ANC	AVL	HRD	REP	OC	IDM
DSP	**0.83**								
LA	.158**	**0.78**							
MA	0.044	.186**	**0.77**						
ANC	0.085	.169**	.103*	**0.78**					
AVL	.143**	.259**	.223**	.103*	**0.77**				
HRD	.213**	.119**	0.044	0.018	.150**	**0.78**			
REP	.225**	.299**	.159**	.269**	.171**	-0.033	**0.82**		
OC	0.022	.204**	.268**	.177**	0.028	-0.061	0.046	**0.75**	
IDM	.141**	.201**	.134**	.220**	.129**	0.030	.213**	.131**	**0.83**