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ARTICLE

Impact of Behavioral Biases on Investment Decisions: Moderating Effect of Preferred Sector of Investment

Shilpi Gupta [1, *] and Monica Shrivastava[2, †]

[1]Amity University, Chhattisgarh and [2]Shri Shankaracharya Group of Institutions, Bhilai

[*]shilpi.sg29@gmail.com
[†]monicasv_1@yahoo.com

Abstract

The study aims to recognize the behavioral biases that influence the decisions making process and investment decisions of retail investors while investing in stocks of insurance and pharmaceutical sector stocks. The paper also aims at checking the moderating effect of the preferred sector of investment on these relationships. The conceptual model derived from past literature was checked for its reliability and validity, using measurement model assessment and structural model assessment. Hypothesis or the study were tested using bootstrapping in PLS-SEM. The result of the study revealed that heuristics and prospects have significant influence, while herd behavior has no significant influence on investor's investment decisions while investing in insurance or pharmaceutical sector securities. The results of the moderation test infer that the relation of heuristic and prospect with investment decision is moderated by the preferred sector of investment. A clear picture of these biases and their influence, established by the findings of the study, would lead to a better understanding of the same and help prevent investors from making erroneous decisions while investing. Investment decisions that are sound and free from behavioral bias, would lead to better financial return, and achievement of investor's investment goals. The sector-wise effect of investment bias will also help the investors in taking corrective measures

Keywords: Behavioral Biases; Retail Investors; Investment Decisions; Heuristics; Prospect

1 Introduction

Economic theories have been evolving, but these theories are always influenced by the assumptions, that humans act rationally while making decisions. What these theories fail to consider is the ever-changing behavioral aspect of the human decision-making process. The ever-changing human psychology plays an important role in the decision-making process. What might influence their decision-making process today may not be equally significant tomorrow. The same is reflected in the field of finance and this is where behavioral finance theories come into play. Studying the impact of psychology on investor's attitudes and behavior is behavioral finance. It is based on the belief that investment decisions of at least a substantial share of investors, if not all, are influenced by behavioral biases, which leads to a lack of rationality behind their investment decisions (Valaskova et al., 2019; Xu, 2014).

In contrast to the conventional theories of economics, which assumed human decisions to be rational and based on proper due diligence before investing, many researchers have indicated that actual investors behave quite differently in practical situations. Traditional finance theories like the efficient market hypothesis believed that an investor always gathers all the necessary information and is impartial in their investment decisions. However, psychologists and recent researchers have indicated that this is not entirely correct as there have been anomalies noticed in the stock market. Babajide and Adetiloye (2012) and Bashir et al. (2013) studied these anomalies and concluded that behavioural finance could explain these anomalies. The field of behavioural finance rose to prominence due to the inability of traditional theories in explaining human behaviour in real situations (Sahi, 2012). Behavioral finance is a rapidly developing area of finance that explains the psychological, conventional economic and financial theories behind an individual's investment decisions (Birău, 2012; Mehmood and D., 2017) Behavioural finance gives a clear idea of the different behavioural biases in the psychological aspect of financial decision-making.

Decisions made under the influence of behavioral biases are often less than optimum in earnings from investment (Shukla et al., 2020). Behavioral biases are psychological anomalies that an investor is susceptible to while taking investment decisions, which leads to irrational decisions and failure in achieving the investment goals (Kapoor and Prosad, 2017). Defined behavioral biases as tools to understand the irregularities from the economic basics of rationality while making an investment decision and referred to these biases as the reason for investors' irrational behavior in investment decisions hindering the growth perspective.

It is established that understanding the impact of these biases on investors' psychology is significant even in modern times. Focusing on these biases would help individual investors improve their performance by overcoming and avoiding the resulting error of judgment (Shabarisha, 2015; Sahi, 2012). There has been a significant increase in the number of investors who are more focused on a handful of investment choices and tend to ignore everything else due to internal biases. With this increased number, understanding the mind of these investors is much more important now, as an unexpected momentum is generated by these investors in the stock market (Wood and Zaichkowsky, 2004).

Based on the views mentioned above the researchers had some questions in mind. What are the different behavioural biases that influence investment decisions? Are these biases that have been discussed over time still existing in financial markets? Do these biases still influence retail investor's investment decisions in financial markets, i.e., are they still significant? The study aims to answer this by assessing and evaluating their current significance in the financial markets and the degree to which they influence a retail investor's investment decisions in the target demographic. Does the preferred sector of investment moderate the relationship of these investment biases with investment decisions? The study aims to identify if the influence of behavioural biases on investment decisions varies based on retail investor's preferences, i.e., their preferred sector of investment in the case of current research. As established, the degree to which these biases influence decision-making varies based on demographic and geographic factors. This study takes into account one such factor which is the preferred sector of investment of retail investors who'll be a part of this study. There is a lack of sector-specific studies of behavioral biases influence on investment decisions. This study attempts to fulfill the gap by examining the influence of behavioral bias on insurance and pharmaceutical sector investment decisions. With all these questions in mind, the researchers in this study sought to recognize the existence and influence of behavioral and inner biases, on retail investors' investment decisions. Thus, the objective of the study was to study the influence of different behavioral biases on the investor's investment decision. The study also aims at assessing the moderating effect of a preferred sector of investment on the relationship between investment biases and decisions. Following the objective of this research, the paper has been organized into five sections. The first section discusses behavioral finance's current outlook, behavioral biases in the stock market and the objective of this study. The second section deals with the conceptual model derived from studying past literature, the research question for this study and its motivation. In the third section, measurement model assessment and structural model assessment and hypothesis testing have been conducted, while the fourth section of the paper covers a brief discussion about the findings and the implications of the research work. The last section covers the conclusions drawn from the study and the limitations and directions for future research.

2 Literature review and hypothesis development

2.1 Heuristics

Behavioral biases first identified by Tversky and Kahneman (1974), are defined as the concept of heuristics, according to which investors tend to depend on their preferences and beliefs when they are unable to deal with the complexity of data analytics (Montier, 2002). Psychology defines heuristics as meek rules that individuals learn based on their own experiences and use as guidelines to make decisions when trapped in multifaceted circumstances (Abreu, 2014). The modern definition of heuristics, states that heuristics are interpretations that force human beings to make decisions that are manageable but based on partial or inadequate knowledge and observant abilities. Valaskova et al. (2019) in their study, state that behavioral finance depends on the application of heuristics and psychological annotations to describe the financial decision-making process, which previously was dependent on mathematical models alone. Over time, heuristics have been further detailed into different types of biases

Overconfidence bias is a tendency of investors to believe that their decisions are better than others even though their performance might be above average at best Nevins (2004); Mehmood and D. (2017). It is observed in investors, who are egotistical, carry indefensible confidence in their usual thoughts, capacities, and decisions (Pompian and

Wood, 2006). It is the unconfirmed and silly confidence in one's conclusion and capacities.

Anchoring is a bias that impacts individuals to reconcile on choices as indicated by a formerly given merit when they try to settle on a decision under vulnerability. Tversky and Kahneman (1974) report the anchoring bias as a condition in which individuals make measures by initiating from a starting value which they alter in accordance to yield a final answer.Andersen (2010) explains anchoring as a common propensity of speculators to depend too particularly on any data for settling on choices in monetary markets. Another heuristic, called confirmation bias, makes individuals in common decipher and support data that affirms the individual's prior ideas (Plous, 1993).

The next heuristic identified is the gambler's fallacy according to which an individual carries a universal belief that one specific result is less liable to take place if it has just happened successively earlier. In the gambler's fallacy, an individual misguidedly accepts that the commencement of a specific irregular incident is more averse to happen following an incident or a progression of incidents. This line of reasoning is erroneous because past incidents do not change the likelihood that specific incidents will happen later (Jayaraj, 2013).

As clear from the past literature, all these biases together define the heuristics that influence investors decisions (Shiller, 1999; Shabarisha, 2015; S. and Yi, 2016). Hence researchers in this study treated heuristics as a second-order formative construct defined by overconfidence bias, representativeness, anchoring bias, confirmation bias, and gambler's fallacy. Throughout the literature review, these five biases were the ones most mentioned. Based on their frequency of occurrence, they've been treated as the first-order constructs that constitute the second-order construct heuristics. Thus, the first hypothesis of this study states:

Hypothesis 2.1. *Heuristics has a significant impact on the investment decisions of retail investors.*

Hypothesis 2.2. *Preferred sector of investment moderates the relationship between heuristics and investment decisions of retail investors.*

2.2 Herd Behavior

Herding, also known as the bandwagon effect, is a bias where the investor's decisions are highly influenced by the decision of others in their surroundings, as they wish to appear to be one of them and be associated with them. This leads to a deviation of asset prices from their fundamental values (Dewan and Dharni, 2019). Shukla et al. (2020) in their study, review different kinds of literature related to herd behavior and the influence herding effect has on investors' decisions and witness varying behavior of herding effect from time to time and across different nations.

Poshkwale & Mandal (2014), in their study, imply that investors exhibit herd behavior more in a bearish stock market, and the behavior keeps on increasing with the expectation of a financial crisis. Whereas, Filip et al. (2015) in their study found that herd behavior is prevalent in both bearish as well as the bullish market. Choi (2016) relates herd behavior to the age factor of investors where older investors easily believe the information provided by relatives and family and follow their advice. Chauhan et al. (2019), in their study, determine that herd behavior is generally prevalent in large-cap stocks and absent in low-cap stocks due to lower volumes of trading in small-cap.

Garg and Gulati (2013); Satish and Padmasree (2018) in their studies contradict the previous theories and conclude that herd behavior is not extant in investors even in crisis periods and imply that herding is not associated with trade volumes. Ripoldi (2016) in their study examines herd behavior in different Chinese stock markets and find that each market has its characteristics with herd behavior as herding effect is present in some market while it is absent in others. Indars et al. (2019) directed a study in the Moscow exchange and observed no herd behavior in the market, barring few times when investors exhibit herd behavior on bearish market days. Given the contradictory results of herd behavior observed in past studies, the researchers in this study sought to check and validate the current scenario of herd behavior in the target demographic. Thus, the second hypothesis of this study is:

Hypothesis 2.3. *Herd behavior has a significant impact on the investment decisions of retail investors.*

Hypothesis 2.4. *Preferred sector of investment moderates the relationship between herd behavior and investment decision of retail investors.*

2.3 Prospect

Prospect theory explains, the decision-making approach investors elect, based on the substitutes concerning risk when they are aware of the results (Shukla et al., 2020). Prospect theory by Kahneman & Tversky and Kahneman (1974) is considered a hugely important concept in behavioral theories. Although many argued the importance of prospect theory, in its initial days, against the traditional expected utility theory, economists have agreed that the prospect theory is quite distinct and prominent in explaining the lack of rationality in human decisions. Shiller (1999); Jayaraj (2013) in their study empirically validates the impact of a loss on human emotions, which is worse than the impact of a gain of the same magnitude. They find that the prospect theory influences more than half of the respondents. Prospect theory mostly deals with the risk and loss side of investment and how humans base their decisions under their influence. Different biases studied under prospect theory are loss aversion, regret aversion, and mental accounting.

Loss aversion, also known as the disposition effect, is an inclination in investors due to which they prefer to sell stocks that have gained in value while holding on to stocks that have lost value (Montier, 2010). Banerji et al. (2020) imply that investors are twice as afraid of losing their investment value against gaining from their investment.

Regret is a feeling that prevails after individuals commend errors. Financial specialists stay away from regret by declining to sell losing stocks and ready to sell budding ones. Besides, financial specialists will in general be progressively contrite about holding losing stocks incredibly long than selling winning ones too early (Fogel and Berry, 2006; Lehenkari and Perttunen, 2004). Normally, individuals weigh just negatives to secure themselves against upcoming misfortunes and ensuing unease. As a result, the possibility of regret affects their investment decisions (Jayaraj, 2013). This habit is called regret aversion, wherein investors are more focused on protecting themselves from losses than earning gains.

Financial specialists who show mental accounting bias will normally treat every factor of their venture portfolio independently. Rather than breaking down a portfolio's total result, they will look at each stock or resource independently Baker et al. (2019); Sewell made clear that mental accounting is the arrangement of mental tasks utilized by individuals and family units to sort out, assess and screen the money-related exercises and exchanges

These three biases, namely loss aversion, regret aversion, and mental accounting, together define the influence of prospects on investors' investment decisions (Dar and Hakeem, 2015; Shabarisha, 2015). Hence in this study, these variables have been combined and converted into a second-order formative construct named prospect. Thus, the third hypothesis of the study is:

Hypothesis 2.5. *Prospect has a significant impact on the investment decisions of retail investors.*

Hypothesis 2.6. *Preferred sector of investment moderates the relationship between prospect and investment decision of retail investors.*

2.4 Preferred Sector of Investment

In a financial market, the choice of securities to invest in is not limited to one or two sectors. In fact, there are multiple sectors or preferences available to any investor to choose from. Investors may prefer one sector over the other based on their past experience, internal perception, or fundamental analysis. An individual who prefers one sector over another may tend to be partial towards its preference when it comes to investment. Certainly, this could lead to ignoring some good choices of investments. Thus, identifying the influence of their sectoral preference on their investment decision is also an important aspect that has been covered in this study's proposed research model as a moderating variable.

In India, there are several insurance companies listed in exchanges. It includes both Government and Private Insurance Organizations. Some of the top insurance stocks listed in Indian exchanges are HDFC Life Insurance, ICICI Prudential Life Insurance, SBI Life Insurance, General Insurance Corporation of India (GIC), ICICI Lombard General Insurance, etc. Indian stock exchanges have both general and life insurance companies listed on them. The highest market cap of one insurance company listed in stock exchanges is as high as 1.15 lakh crore (www.moneycontrol.com/stocks/marketinfo), implying insurance sector securities to be a sizeable chunk of investment in India.

The other sector of investment considered as a sampling unit for this study is the pharmaceutical sector. There are more than 100 pharmaceutical companies listed in Indian stock exchanges. Some of the big companies, according to their market cap, listed are Sun Pharma, Dr. Reddy's Lab, Divis Lab, Cipla, Aurobindo Pharma, etc. The market cap of the largest pharmaceutical company listed on the Indian stock exchange, i.e., Sun Pharma is 1.16 lakh crore followed by Dr. Reddys Lab in second place with a market cap of 83,990 crores (www.moneycontrol.com/stocks/marketinfo). The pharmaceutical sector also has penny stock with a market cap of 1-2 crore only. Given the huge number of pharma companies listed with market caps of many being quite high and their sheer volume of trade, the pharma industry is a major chunk of investment for retail or individual investors.

3 Research Methodology

The survey instrument, i.e., the questionnaire used for the study, consisted of 37 items adopted from existing literature of behavioural biases as depicted in Table 1. These items measured the level of different behavioural biases related to investment decisions. The response to the items was recorded on a seven-point Likert scale. The questionnaire was divided into two sections. The first section of the questionnaire had questions related to the respondent's demographics, while the second part of the questionnaire had items that measured the level of different behavioural biases in the respondent.

The target population of the study was investors, who are active investors of either insurance sector stocks or pharmaceutical sector stocks. Data was collected from investors of Chhattisgarh, India, for one and a half months. The data were collected through a mail survey and personal interview. Purposive sampling was employed, and a total of 384 responses were collected. In the initial phase of the study, the sample size was determined using G-Power 3.1 software. With nine independent variables, an expected effect size (f^2) value of at least 0.05, and

Table 1. Papers Reviewed for Item Generation

S. No.	Factor	Reference
1	Overconfidence Bias	Odean (1998), Scheinkman et al. (2003), Glaser et al. (2007), Jayaraj (2013), Shabarisha (2015), Bakar & Yi (2016), Hassan et al. (2016), Shukla et al. (2020)
2	Representativeness	Ritter (2003), Shefrin (2007), Jayaraj (2013), Shabarisha (2015), Hassan et al., Pompian and Wood (2006), Banerji et al. (2020), (2020), Shukla et al. (2020)
3	Gambler's Fallacy	Shiller (1999), Jayaraj (2013) , Shabarisha (2015), Banerji et al.,
4	Anchoring Bias	Tversky and Kahneman (1974), Kaustia et al., (2008), Jayaraj (2013), Shabarisha (2015) , Bakar & Yi (2016), Banerji et al., (2020), Shukla et al. (2020)
5	Confirmation Bias	Jayaraj (2013), Shabarisha (2015), Banerji et al., Shukla et al. (2020),
6	Loss Aversion	Shiller (1999), Hwang et al., (2010), Jayaraj (2013), Shabarisha (2015), Banerji et al. (2020), Shukla et al. (2020)
7	Regret Aversion	Shiller (1999) , Jayaraj (2013), Sahi (2012), Shabarisha (2015), Banerji et al., (2020)
8	Mental Accounting	Shiller (1999), Barber and Odean (2013), Jayaraj (2013), Shabarisha (2015), Shukla et al. (2020)
9	Herd Behaviour	Garg and Gulati (2013), Poshakwale and Mandal (2014), Ripoldi (2015), Choi (2016), Hassan et al., (2016), Banerji et al., (2020),Shukla et al. (2020)
10	Investment Decision	Shiller (1999) , Sahi (2012), Bakar & Yi (2016), Banerji et al., (2020), Shukla et al. (2020)

statistical power of 95 percent, it was determined that a sample size of a minimum of 262 observations should be sufficient for the study Faul et al. (2007, 2009). After checking the completeness of data, 323 usable responses were retained, which satisfied the criteria of having at least 262 respondents.

4 Data Analysis

Table 2 presents the demographic profile of the respondents. It is evident from the table that any type of bias arising due to a large number of respondents from a single category was avoided across all the demographics. Out of the 323 respondents, 46 percent were male, and 54 percent were female investors. 53 percent preferred to invest in insurance sector stock while the other 47 percent preferred investing in pharmaceutical companies listed on the stock exchange. Thirty-one percent of the respondents were from 36-45 age groups, while 26 percent, 29 percent, and 14 percent were from 26-35, 46-55, and above 55 age groups.

4.1 Measurement Model Assessment

The model consisted of both first and second-order constructs, where the first-order constructs were reflective in nature, and the second-order constructs were formative. In the first part of data analysis, the first-order constructs were checked for their reliability and validity. PLS-SEM was employed using Smart PLS 3.3.2 (Ringle et al., 2015) following the two-stage systematic procedure prescribed by Anderson and Gerbing (1988).

The first step in the measurement model assessment was to check the convergent validity and composite reliability of the model. Table 3 shows the values of factor loadings, composite reliability (CR), average variance extracted (AVE), Cronbach's alpha, and Dillion-Goldstein's rho (rho_A). The factor loading of all items except HRDB1 and RGAV1 was above 0.7. HRDB1 and RGAV1 were retained even though their loadings were less than 0.7 because the AVE and CR values of both the constructs, herd behaviour, and regret aversion, were sufficient to fulfil the criteria suggested by Hair et al., (2017) for measurement model assessment. CR and rho_A values of the constructs were more than the threshold value of 0.7; internal reliability was achieved in the model. Another reliability measure is Cronbach's alpha value, where a value of more than 0.7 represents excellent reliability. From the results of the measurement model assessment, all the constructs' alpha values were above the threshold value of 0.7, and hence, reliability criteria were satisfied. AVE values of more than 0.5indicated the convergent validity of the constructs.

Table 2. Respondents Profile

Demographic Variable	Category	Frequency	Percentage
Age	26-35	84	26%
	36-45	100	31%
	46-55	94	29%
	Above 55	45	14%
Gender	Male	149	46%
	Female	174	54%
Preferred sector of investment	Insurance Sector	171	53%
	Pharmaceutical Sector	152	47%

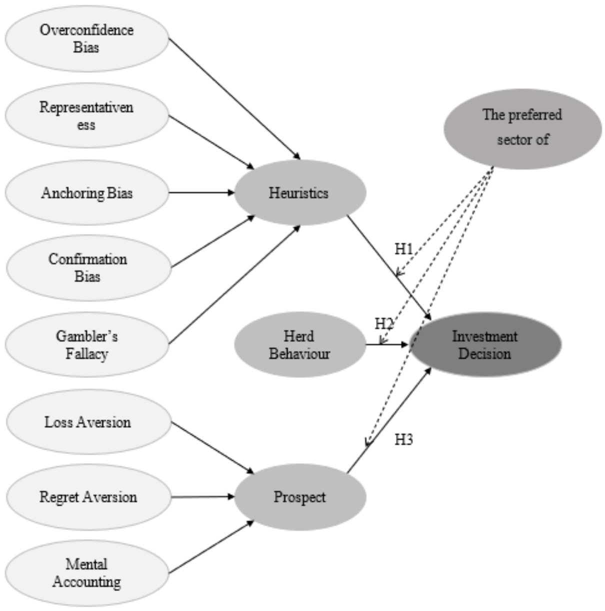

Figure 1. Conceptual Model

Looking at the results in Table 3, it can be concluded that convergent validity was achieved for the constructs in this study

After assessing the convergent validity of the constructs, next step was to check the discriminant validity, for which two criteria are suggested, namely, Fornell-Larcker criterion and heterotrait – monotrait ratio of correlations (HTMT). According to the first criteria for discriminant validity, (Fornell and Larcker, 1981) the square root of a construct's AVE value should be higher than the correlation coefficient, of that construct, with other constructs in the model. The discriminant validity assessment results shown in Table 4 show that discriminant validity was achieved, as the criteria suggested by Fornell & Larcker (1981) were satisfied for all the constructs.

Researchers in past literatures have implied that HTMT approach by Henseler et al. (2015) for assessing discriminant validity is better compared to Fornell-Larcker criterion, as HTMT approach is proven to achieve better sensitivity and specificity rate Xia and Cheng (2017); Rasoolimanesh et al. (2019). According to HTMT criterion, all the calculated values of construct should be less than 0.9 to achieve discriminant validity Henseler et al. (2015); Voorhees et al. (2016). Seeing the HTMT results in Table 5 shows that all the values satisfy the criteria for achieving discriminant validity. The model has displayed enough reliability and validity from the overall results of measurement model assessment.

4.2 Structural Model Assessment

In the first step of structural model assessment and hypothesis testing, collinearity issue was checked using the variance inflation factor (VIF). The calculated VIF values for all the constructs lied in the range of 1.184-2.50. According to the criteria suggested by Diamantopoulos and Siguaw (2006) the values should be less than 3.33, and according to the criteria suggested by Hair et al., (2017), the VIF values should be less than 5. Calculated values of VIF prove that no collinearity issue existed in the model as all the values were less than 3.33. Also as suggested by Kock (2015), the VIF values below 3.3 prove that model is free from the common method bias.

Then, the hypotheses were tested using a bootstrapping technique with a subsample size of 5000. Bootstrapping

Table 3. Measurement Model Assessment Results

Construct	Items	Type	Loading/ Weight	CR	Cronbach's Alpha	rho A	AVE
ANBS	ANBS1 ANBS2 ANBS3	Reflective	0.945 0.871 0.847	0.918	0.866	0.868	0.79
CNFB	CNFB1 CNFB2 CNFB3	Reflective	0.833 0.763 0.831	0.851	0.736	0.74	0.655
GAMF	GAMF1 GAMF2 GAMF3 GAMF4	Reflective	0.841 0.900 0.818 0.925	0.927	0.894	0.898	0.761
HRDB	HRDB1 HRDB2 HRDB3 HRDB4	Reflective	0.632 0.817 0.735 0.773	0.83	0.726	0.738	0.551
INVD	INVD1 INVD2 INVD3 INVD4	Reflective	0.826 0.856 0.782 0.842	0.896	0.846	0.847	0.684
LSAV	LSAV1 LSAV2 LSAV3	Reflective	0.732 0.873 0.888	0.872	0.779	0.8	0.696
MACC	MACC1 MACC2 MACC3	Reflective	0.867 0.766 0.869	0.874	0.783	0.795	0.698
OVRB	OVRB1 OVRB2 OVRB3 OVRB4	Reflective	0.805 0.895 0.879 0.910	0.928	0.896	0.9	0.763
RGAV	RGAV1 RGAV2 RGAV3 RGAV4	Reflective	0.554 0.853 0.883 0.775	0.856	0.773	0.812	0.604
REP	REP1 REP2 REP3 REP4	Reflective	0.849 0.853 0.851 0.924	0.926	0.893	0.895	0.757
HRISTC	OVRB REP GAMF ANBS CNFB	Composite	0.149 0.376 0.296 0.254 0.244	NA	NA	NA	NA
PRSPCT	LSAV RGAV MACC	Formative	0.390 0.493 0.328	NA	NA	NA	NA

ANBS: Anchoring Bias; CNFB: Confirmation Bias; GAMF: Gambler's Fallacy; HRDB: Herd Behavior; INVD: Investment Decision; LSAV: Loss Aversion; MACC: Mental Accounting; OVRB: Overconfidence Bias; RGAV: Regret Aversion; REP: Representativeness;

results displayed that, heuristics and prospect had a positive significant impact on investor's investment decisions with (β = 0.517, t = 8.797) and (β = 0.309, t = 5.131) respectively. Following these outcomes, hypotheses H1 and H3 were supported. It was observed that herd behaviour with (β = 0.015, t = 0.301) did not impact investment decisions, and hence hypothesis H2 was not supported.

Table 4. Discriminant Validity Assessment (Fornell-Larcker Criterion)

	ANBS	CNFB	GAMF	HRDB	INVD	LSAV	MACC	OVRB	RGAV	REP
ANBS	0.889									
CNFB	0.618	0.809								
GAMF	0.313	0.467	0.872							
HRDB	0.297	0.607	0.468	0.742						
INVD	0.567	0.705	0.446	0.471	0.827					
LSAV	0.413	0.616	0.403	0.389	0.583	0.834				
MACC	0.444	0.507	0.302	0.473	0.459	0.412	0.836			
OVRB	0.393	0.267	0.122	0.201	0.148	0.217	0.2	0.873		
RGAV	0.517	0.677	0.44	0.454	0.675	0.624	0.467	0.204	0.777	
REP	0.52	0.654	0.585	0.472	0.651	0.559	0.357	0.214	0.641	0.87

ANBS: Anchoring Bias; CNFB: Confirmation Bias; GAMF: Gambler's Fallacy; HRDB: Herd Behavior; INVD: Investment Decision; LSAV: Loss Aversion; MACC: Mental Accounting; OVRB: Overconfidence Bias; RGAV: Regret Aversion; REP: Representativeness;

Table 5. Discriminant Validity Assessment (HTMT Criterion)

	ANBS	CNFB	GAMF	HRDB	INVD	LSAV	MACC	OVRB	RGAV	REP
ANBS										
CNFB	0.773									
GAMF	0.354	0.573								
HRDB	0.367	0.829	0.572							
INVD	0.661	0.88	0.506	0.589						
LSAV	0.496	0.806	0.473	0.525	0.71					
MACC	0.544	0.665	0.363	0.624	0.561	0.517				
OVRB	0.448	0.319	0.128	0.24	0.175	0.251	0.234			
RGAV	0.615	0.879	0.53	0.596	0.82	0.795	0.566	0.237		
REP	0.591	0.806	0.651	0.581	0.745	0.668	0.426	0.232	0.768	

ANBS: Anchoring Bias; CNFB: Confirmation Bias; GAMF: Gambler's Fallacy; HRDB: Herd Behavior; INVD: Investment Decision; LSAV: Loss Aversion; MACC: Mental Accounting; OVRB: Overconfidence Bias; RGAV: Regret Aversion; REP: Representativeness;

After the hypothesis testing, the value of the coefficient of determination (adjusted R square) was evaluated. The calculated adjusted R square value of 0.621 was above 0.26, which inferred substantial predictive precision of the model Cohen (1988). The effect size (f^2) of the constructs was examined using criteria suggested by Cohen (1988), according to which value of more than 0.35 inferred colossal effect size, the value between 0.15-0.35 inferred moderate effect size and values less than 0.15 inferred minor effect size..

Table 6. Hypothesis Testing Results

	Relationship	Std. β	t-value	Confidence Interval	Effect Size (f^2)	Supported
H1	Heuristics à Investment Decision	0.517	8.797	[0.394,0.624]	0.255	Yes
H2	Herd Behaviour à Investment Decision	0.015	0.301	[-0.083,0.109]	0.001	No
H3	Prospectà Investment Decision	0.309	5.131	[0.192,0.425]	0.100	Yes

With reference to investment decision, heuristics (f^2 = 0.255) had medium effect and prospect (f^2 = 0.100) had minor effect. Herd behaviour had a negligible effect on investment decisions, as proven by the results of bootstrapping. The standard root means square residual value (SRMR) for the model was 0.07, less than the recommended maximum threshold of 0.08 (Hu and Bentler, 1999), which showed an acceptable model fit.

In the last step of the analysis, predictive relevance was calculated using the blindfolding technique, with an omission distance of seven. The results were assessed using Stone-Geisser's Q^2 value (Garg and Gulati, 2013;

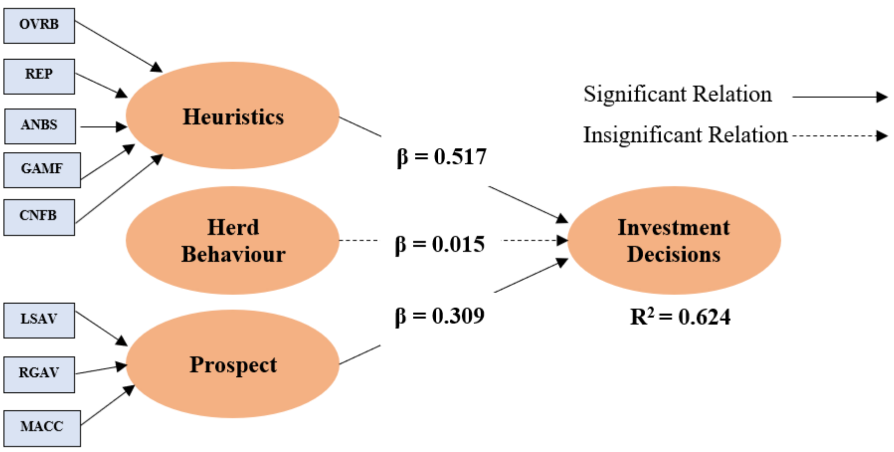

Figure 2. Structural Model with Second-Order

OVRB: Overconfidence Bias; REP: Representativeness; ANBS: Anchoring Bias; GAMF: Gambler's Fallacy; CNFB: Confirmation Bias; LSAV: Loss Aversion; RGAV: Regret Aversion; MACC: Mental Accounting;

Geisser, 1974; Stone, 1974). The calculated Q^2 value for investment decisions was 0.412, which was significantly more than zero. Hence it was established that the model had satisfactory predictive relevance.

4.3 Moderating Role of Preferred Sector of investment:

The moderating effect of the preferred sector of investment was assessed using multi-group analysis (MGA) using Smart PLS 3.2.2 software. The proposed research model tries to test the moderating effect of the preferred sector of investment on the relationship between heuristic, prospects, and herd behaviour on investment decisions of retail investors. The respondent profile data reveal that out of 323 respondents, 171 preferred investing in the Insurance sector while the remaining 141investors preferred to invest in the pharmaceutical sector. The R2 value reported for investors of the insurance sector is 0.628 and that of the pharmaceutical sector is 0.630. The result represented in Table 7 confirms that the preferred sector of investment does moderate the relationship of heuristic and prospect with the investment decision of retail investors. However, the relationship between herd behaviour and investment decision is not moderated by the preferred sector of investment. The investors of the pharma sector (β = 0.552) were more prone to heuristics bias as compared to the investor of the insurance sector (β = 0.478). The investor of the pharma and insurance sector are equally affected by the prospect bias as reported by their beta values, i.e., β = 0.305 for pharma and β = 0.310 for insurance.

Table 7. Moderating Effect of Preferred Sector of investment – MGA

	Path Coefficients Original (INSURANCE)	Path Coefficients Original (PHARMA)	Path Coefficients Mean (INSURANCE)	Path Coefficients Mean (PHARMA)	STDEV (INSURANCE)	STDEV (PHARMA)	t-Value (INSURANCE)	t-Value (PHARMA)	p-Value (INSURANCE)	p-Value (PHARMA)
Herd Behaviour -> Investment Decision	0.073	-0.026	0.072	-0.021	0.071	0.069	1.031	0.374	0.302	0.709
Heuristics -> Investment Decision	0.478	0.552	0.482	0.556	0.100	0.062	4.806	8.861	0.000	0.000
Prospects -> Investment Decision	0.310	0.305	0.316	0.310	0.095	0.071	3.276	4.294	0.001	0.000

5 Discussions & Implications

The study commenced with a brief review of past literature on behavioral biases and their impact on retail investor's investment decisions in insurance and pharmaceutical sector securities. A second-order model was developed based on the literature review, and the model was assessed for its reliability and validity. The results of the study offered conclusions about the influence of heuristics, prospect, and herding effect on retail investor's investment decisions.

The first category of bias being tested was heuristics, which was conceptualized as a second-order construct. In this study, heuristics were defined by overconfidence bias, confirmation bias, anchoring bias, gambler's fallacy, and representativeness bias. The results indicated that heuristics bias significantly influenced the retail investor's investment decisions in pharmaceutical and insurance stocks. The studies of Sahi (2012), supported the existence of these biases (Shukla et al., 2020) . The results indicating a strong influence of heuristics on investment decisions were in line with studies conducted by Chen et al. (2007); Boda et al. (2016) who in their study concluded that heuristics have a significant impact on investor's investment decisions and it often led investors to make trading mistakes. Under the influence of heuristics biases, investors often believe in their decision more than others, focusing on their recent experiences ignoring the past returns. They tend to rely significantly on a particular piece of information regardless of its reliability and affirm their stance based on their existing knowledge. The need is for these investors to understand the errors that could results due to these notions that they carry. A clear understanding of heuristics would, in general, help them make better informed and less erroneous decisions.

The second category of bias that significantly influenced the retail investor's investment decisions was prospect bias. As per the prospect theory, investors often look to avert risk and regret, due to investment decisions as much as possible when they are aware of the expected return; they can achieve from different substitutes of investment choices. While investing, individuals weigh in both the outcomes of an investment viz—possible losses and gains. Investors are often inclined towards avoiding loss more than they are towards earning better gains. The results of this study demonstrate that prospect constructs still influence investor's decision-making process, though not as significantly as heuristics. These results are supported by previous studies conducted Oechssler et al. (2009), conforming to the prospect theory. Taking note of this prospect, investors could focus on both the gain and loss aspects of investment equally instead of focussing on just the probability of loss. A decision free from this bias should lead to an optimal investment decision.

The last bias assessed in this study was herd behaviour, also known as the bandwagon effect. Under the influence of this bias, investors rely on their friends, family, and peer's investment decisions even though they may lack credibility. This study indicated that herd behaviour does not influence the investment decision of retail investors, trading in the stock of insurance and pharmaceutical stocks. Researchers in the past have observed different results between the relationship of herding and investment decisions. Some researchers supported the influence of herd behaviour on investment decisions in a bearish or bullish market, influenced by the age of investors and value of the stock (Filip et al., 2015; Choi, 2016; Chauhan et al., 2019). While other researchers have denied the existence of such influence regardless of the demographic, value of the stock, and market trend Garg and Gulati (2013); Indars et al. (2019). Moderation results draw a clear picture confirming that investors behave differently when investing in different sectors of investment. For some sectors, investors may be more prone to heuristics while some may be more influenced by the prospect. Thus, taking note of this is equally significant as focussing on the bias itself is. The results of this study add to this discussion, evidently supporting the absence of herd behaviour amongst insurance and pharmaceutical stock investors of Chhattisgarh even though the relation between herding and investment decision, to an extent, may exist in investors of other sectors or demographics.

This research has several implications that could be drawn for academicians as well as retail investors and investment managers. For academicians, the survey instrument, i.e., the questionnaire used in the current research works can also be employed in other demographics or geographies to study the influence of these vital biases in the same. The study and model developed in it can be used for teaching the positioning of these biases in today's market. The results of this study would help expand the understanding of behavioural biases and their influence on investment decision-making and help explain how the biases generated based on external prospects like aversion and internal preferences like heuristics could influence investment decisions. The model developed in this study could also be used to analyse the influence of behavioural biases on investment decisions of investors whose preferred sector of investment is other than pharmaceutical or insurance.

For retail investors and investment managers, the research findings give a clear picture of the current state of heuristics, prospect, and herd behaviour in insurance and pharmaceutical sector investment. Consequently, a clear picture of these biases and their influence would lead to a better understanding of the same and prevent investors from making erroneous decisions. Behavioural biases are accountable for numerous irregularities in stock markets. Thus, it is quite substantial to realize the stimulus of these partialities on investment decisions. The results of this study would help realize these partialities. A strong understanding of these biases and their influence on investment decisions could help financial planners and advisors to provide optimized and adequate investment advice. It would help financial planners and advisors understand how their client's investment decisions are driven.

6 CONCLUSION

This research tried to identify the different biases that influence retail investor's decisions to invest in securities of insurance and pharmaceutical companies. To study this subject, a second-order model was developed based on the three primary areas of behavioural biases, namely heuristics, prospect, and herding. The model was assessed and validated in two stages, measurement model assessment and structural model assessment. The main objective of the study was to identify whether these biases are still existent in the retail investor's psychology before investing in insurance and pharmaceutical company stocks. It was determined that heuristics and prospect bias have a massive impact on investor's decisions, with heuristics influencing the decisions more than prospects. Results also indicated an absence of herd behaviour's influence on investment decisions amongst investors of the insurance and pharmaceutical sector. This study contributed to the existing literature by looking into the current state of these biases in the financial market and drawing conclusions for a better understanding of investor behavior in insurance and pharmaceutical sector stocks. The study had some limitations of its own. The first being that, it only considered active investors of insurance and pharmaceutical securities and it was limited to investors of Chhattisgarh, India. Future research can be conducted to identify the current state of these biases in a different demographic and sectors other than the insurance and pharmaceutical sectors.

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