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"THE IMPACT OF BEHAVIORAL BIAS ON INVESTMENT DECISION ON THE BASIS OFEXPERIENCE OF INVESTOR"

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Abstract: The study titled "The impact of behavioral bias on investment decision on the basis if experience of investor" rigorously examines the pervasive influence of behavioral biases on investment decision-making within the context of the experience of the investor. This study delves into the variations in biases across investors of different experience levels. The analysis presented in this chapter stems from data gathered through a structured questionnaire distributed among 450 investors operating in the tricity region (Chandigarh, Mohali, and Panchkula). By examining the responses collected, insights into how biases manifest differently depending on the investors' levels of experience are sought.

Keywords: Behavioral bias, finance, experience, decision making, earning.

INTRODUCTION

The study of behavioral finance has shed light on how human biases significantly influence investment decisions, challenging traditional views of rationality and marketefficiency. Various biases, including cognitive and emotional ones like mental accounting, anchoring, loss aversion, and herding, often lead investors away from rational decision-making. In the Indian stock market, where cultural nuances and socio-economic factors play significant roles, understanding these biases becomes even more crucial. From the allure of quick gains to the fear of missing out,

behavioral biases profoundly impact individual strategies and overall market dynamics, emphasizing the need for a nuanced approach to decision-making.

The study shows that experience is important for changing investors' behavioural biases. This is useful information for finance professionals, lawmakers, and researchers. The results have implications for how to invest, how to handle risk, and how to help people make better financial decisions by reducing the negative effects of behavioural biases. The study's main goal is to improve our knowledge of howinvestors act and help make better, more informed financial decisions by using rigorous testing and analysis of real-world data.

REVIEW OF LITERATURE

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Malmendier et al.(2020) Macrofinancial shocks changed investor behavior and market dynamics, as revealed by research on experience effects. Directly experienced outcomes have a lasting impact on investors' views and decisions, with significant differences observed between older and younger generations. The formalization of experience-based learning in an overlapping generations (OLG) model elucidates howviews, portfolio choices, and trade patterns differ over time due to varied cohort experiences. The model unveils a novel connection between investor types and price dynamics influenced by past payouts. The findings align with established insights on asset prices, including volatility, return predictability, and reactions to crises.

Ismiyanti et al.(2020)in this study, he explained that Chou et al. (2010) examined financial experience, risk propensity, and risk perception, laying the groundwork for this study. Expanding on their work, this research delved into the influence of investment experience on return expectations and its interaction with risk propensity. The study revealed that investment experience heightened risk propensity, reducing risk perception and elevating return expectations. Notably, a connection emerged between risk perception and expected returns, particularly among small investors favoring technical analysis over fundamental analysis. This trend suggested an increasing preference for short-term trading activities among individual investors.

Gupta et al.(2019) The study aimed to investigate investor behavior in market-wide sentiment and herding. Utilizing a dynamic factor model to analyze latent factors

influencing asset returns, the research found that behavioral factors significantly contribute to changes in asset prices, with varying impact across stocks and portfolios.The data supported the idea that behavioral factors are more important for high- and medium-value stocks than for low-value stocks.

OBJECTIVES OF THE STUDY

The study was conducted taking into consideration the following objectives:

1. To understand the bias that affects investment decisions.
2. To compare the influence of bias on the basis of experience of investor.

RESEARCH MODEL

Null Hypotheses (H0): There is no significant difference in the impact of behavioral biases on investment decisions between novice and experienced individual investors in the Indian stock market.

Alternative Hypotheses (H1): There is a significant difference in the impact of behavioral biases on investment decisions between novice and experienced individual investors in the Indian stock market.

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Ten more hypotheses, labelled H1(a) through H1(J), were made to help with the goal of comparing the effect of bias based on investors' experience. The purpose of these theories is to find out how the independent variable (investors' experience) related to different dependent variables (behavioural biases). The crux of these hypotheses lay in elucidating how the level of experience among investors affected their susceptibility to different behavioral biases. By empirically testing these hypotheses, insights into the nuanced impact of investor experience on behavioral biases were provided.

- Hypotheses 1(a): Investment experience has a positive influence on self-controlbias.
- Hypotheses 1(b): Investment experience has a positive influence onavailabilitybias.
- Hypotheses 1(c): Investment experience has a positive influence onover-confidence bias.
- Hypotheses 1(d): Investment experience has a positive influence on representative/ familiarity bias.
- Hypotheses 1(e): Investment xperience hasloss-aversion bias. a iegative influ nce ι
- Hypotheses 1(f): Investment xperience hasmental-accounting bias. a iegative influ nce ι
- Hypotheses 1(g): Investment experience has a positive influence on RegretAversion bias.
- Hypotheses 1(h): Investment experience has a positive influence on aAnchoringbias.
- Hypotheses 1(i): Investment experience has a negative influence on self-attributebias.
- Hypotheses 1(j): Investment experience has a negative influence on Herdingbias.

DATA ANALYSIS AND INTERPRETATION

This study used information from surveys that were sent to up to 450 people. The indicator for each variable was good because it had a Cronbach Alpha number above 0.6, which means it was pretty reliable. The data from all 450 respondents was checked for the good fit score. For the test, two types of models were used: models formeasuring and models for building. Investor action bias was the dependent variable that was linked to a number of different measures to make the measurement model.

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1. Measurement Model Test

The table 1 presents the fit measurement model test results, which are crucial in evaluating the effectiveness of a structural equation model (SEM) in explaining the relationships between variables. Each indicator in the table offers insights into
different aspects of the model's fit.

To see if the measurement model worked well, Table 6.1 displays six indicators: Chi- square, RMSEA, AGFI, CMIN/DF, TLI, and CFI. These indicators had good fit information or met the standards. In this case, GFI was a fit indicator that was only somewhat good, while the measure model fit indicator was a good fit indicator. There is faith in the model's ability to explain the observed data well because other indicators are generally consistent.

Table 1: Fit Measurement Model Test Results

. .	**Indic tors**	**Full form of fitness Indices**	**Criteria**	**R sult**	**No e**
	Chi- quare	(χ^2)	Small xpected	5 .29	Go d fit
	RMS A	Root Mean Square rror of Approximation	RMSEA = 0.08	0. 00	Go d fit
	GFI	Goodness of Fit ndex	GFI >= .90	0. 34	Go d fit
	AGF	Adjusted Goodness f Fit Index	AGFI >= .90	0. 54	Ma ginal fit
	CMI /DF	Chi-Square inimum/ Degrees of reedom (also known as ormed Chi-Square)	CMIN/D <= 2	0. 37	Go d fit
	TLI	Tucker-Lewis ndex (also known as Non- ormed Fit Index, NNFI)	TLI >= 0.90	1. 56	Go d fit
	CFI	Comparative Fit ndex	CFI >= .90	1. 58	Go d fit

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There are notes in Table 1, that say whether the fit of the measuring model is good or marginal for each dependent variable. The adequateness of the measurement model is checked using two important indicators: Composite Reliability (CR) and Average Variance Extracted (AVE).

This measure checks how reliable the constructs are on an internal consistency level, starting with Composite Reliability (CR). A CR value greater than 0.70 is typically considered acceptable, indicating that the items comprising each variable reliably measure the underlying construct. In this table, all dependent variables except for "Mental Accounting Bias" have CR values exceeding the threshold, suggesting good internal consistency reliability.

Average Variance Extracted (AVE) checks whether the constructs are convergent by looking at how much of the variance is caught by the indicators compared to measurement error. Values of AVE greater than 0.50 show good convergent validity, showing that the markers correctly reflect the hidden concepts. In this table, alldependent variables meet or exceed the 0.50 threshold for AVE, indicating good convergent validity.

Based on these criteria, most of the dependent variables demonstrate a good fit in the measurement model. Specifically, "Self-Control Bias," "Availability Bias,""Overconfidence Bias," "Representative/Familiarity Bias," "Loss Aversion Bias," "Regret Aversion Bias," "Anchoring Bias," "Self-Attribution Bias," and "Herding Bias" all exhibit CR and AVE values indicative of good fit. However, one exception is"Mental Accounting Bias," which shows a CR value below the threshold, indicating marginal internal consistency reliability. While the AVE value for "MentalAccounting Bias" meets the threshold for convergent validity, the lower CR value suggests that the indicators for this variable may not be as reliable in measuring the underlying construct compared to other variables.

Table 2: Measurement Model Fit For Dependent Variables

S.No.	Dependent Variables	8. Measurement Model Fit		Result
		Composite Reliability CR > 0.70	Average Variance Extracted AVE > 0.50	
1.	**Self-Control Bias**	0.794	0.725	Good Fit
2.	**Availability Bias**	0.817	0.628	Good Fit

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3.	**Overconfidence Bias**	0.718	0.583	Good Fit
4.	**Representative/ Familiarity Bias**	0.825	0.519	Good Fit
5.	**Loss Aversion Bias**	0.728	0.518	Good Fit
6.	**Mental Accounting Bias**	0.645	0.478	Marginal Fit
7.	**Regret Aversion Bias**	0.710	0.598	Good Fit
8.	**Anchoring Bias**	0.785	0.618	Good Fit
9.	**Self-Attribution Bias**	0.728	0.518	Good Fit
10.	**Herding Bias**	0.829	0.592	Good Fit

2. Structural Model Test

The structure model, the second model, is now being put to the test. The dependent variable in the structure model will be behavioral biases like overconfidence, lack of self-control, following the crowd, and so on. Experience with money will be the independent variable. This is done so that we can see what these two factors do.

The table 3, presents the results of fit measurement indicators used to assess the adequacy of a structural equation model (SEM). These indicators are essential in determining whether the model adequately represents the relationships between variables. Each indicator is evaluated against specific criteria to determine if the fit is considered good or marginal. Looking at the Chi-square indicator first, it checks how different the observed and predicted covariance matrices are from each other. A betterfit is shown by a smaller chi-square number. The chi-square value of 236.061 in this case shows a good fit, which means that the model correctly describes the observed data.

A good fit is shown by most indicators, such as Chi-square, RMSEA, AGFI, CMIN/DF, and CFI. This means that the model accurately describes the observed data.However, the GFI and TLI indicators show marginal fit. Despite these discrepancies, the overall evaluation leans towards a good fit for the model, suggesting its

effectiveness in explaining the relationships between variables.

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Table 3. Result of Fit Structural Model Test

S. no.	Indicators	Criteria	Result	Note
1	**Chi-square**	Small expected	236.061	Good fit
2	**RMSEA**	RMSEA <= 0.08	0.050	Good fit
3	**GFI**	GFI >= 0.90	0.826	Marginal fit
4	**AGFI**	AGFI >= 0.90	0.989	Good Fit
5	**CMIN/DF**	CMIN/DF <= 2	0.561	Good fit
6	**TLI**	TLI >=0.90	0.814	Marginal fit
7	**CFI**	CFI >= 0.90	0.951	Good fit

In Table 4, you can see how well the structure model fits each dependent variable. This shows that the measurement model is safe and correct. The Average Variance Extracted (AVE) and the Composite Reliability (CR) are two important ways to look at things. The AVE level is set at 0.50 and the CR level is set at 0.70. You can use these signs to tell if the model is good at figuring out what the variables really mean.

It looks like most of the dependent variables fit well with the data when you look at the CR and AVE factors. The Overconfidence Bias, the Loss Aversion Bias, the Regret Aversion Bias, the Anchoring Bias, the Self-Attribution Bias, and the Herding Bias are some of the different kinds of these flaws. The AVE value for each of theseis over 0.50 and the CR value is over 0.70. This means that these variables are very consistent with each other, and the underlying models can explain the observed variables' variation well, showing a good fit.

The variable Mental Accounting Bias, on the other hand, only barely fits. While its AVE value is above the 0.50 mark, its CR value is below the 0.70 mark that it should be. In other words, there may be some problems with how reliable the data is for this variable. A weak fit means that the Mental Accounting Bias measurement model may need to be looked at more closely to make sure it is true and reliable within the overall

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structural model.

Table 4: Structural Model Fit (CR AND AVE)

S.No.	Dependent Variables	8. Measurement Model Fit		Result
		Composite Reliability CR > 0.70	Average Variance Extracted AVE > 0.50	
1.	Self-Control Bias	0.826	0.834	Good Fit
2.	Availability Bias	0.719	0.692	Good Fit
3.	Overconfidence Bias	0.790	0.627	Good Fit
4.	Representative/ Familiarity Bias	0.878	0.567	Good Fit
5.	Loss Aversion Bias	0.789	0.523	Good Fit
6.	Mental Accounting Bias	0.623	0.367	Marginal Fit
7.	Regret Aversion Bias	0.790	0.534	Good Fit
8.	Anchoring Bias	0.734	0.678	Good Fit
9.	Self-Attribution Bias	0.789	0.534	Good Fit
10.	Herding Bias	0.899	0.589	Good Fit

In evaluating the adequacy of a research model, the focus is typically on several fit indices to assess whether the model effectively captures the relationships between variables. Most of the time, at least three to four indicators meeting the set standards are enough to make an index good. This ensures a robust and reliable model that accurately represents the underlying constructs. In this project, we tested both the measurement model and the structure model. Six of the measurement model's markersmet the

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needs for a good fit, which was more than most of the time. This suggests that the measurement model effectively captures the latent constructs under investigation. Additionally, one indicator fell within the criteria for marginal fit, indicating a minor deviation but not necessarily compromising the overall adequacy of the model.

In the same way, four indicators in the structural model met the standards for a good fit. This showed that the model could accurately show how the variables were related. However, two indicators showed marginal fit, suggesting some minor issues with reliability or validity in specific aspects of the model.

On the whole, the data show that the model mostly fits well with both the measurement and structural models. This suggests that the model is well-grounded and provides a solid foundation for further hypothesis testing. Despite the minor deviations observed in some indicators, the overall adequacy of the model supports the continuation of hypothesis testing, allowing for further exploration and validation of the hypotheses.

HYPOTHESES TESTING

Table 5: Hypotheses Testing

Hypotheses		**Esti nate**	**p- alue**	**Hypotheses testing**
H1( )	Investment xperience to Self-Control	0.85	0.04 *	Accepted
H1( )	Investment xperience to Availability	- .097	0.03	Accepted
H1( )	Investment xperience to Overconfidence	0.44	0.46	Rejected
H1(l)	Investment xperience to Representative/Fami iarity	0.13	0.50	Rejected
H1( )	Investment xperience to Loss Aversion	- .122	0.05 **	Accepted

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H1( )	Investment xperience to Mental Accounting	-).296	0.00)***	Accepted
H1(;)	Investment xperience to	0.25	0.57	Rejected
	Regret Aversion			
H1(ı)	Investment xperience to Anchoring	-0.14	0.02	Accepted
H1( )	Investment xperience to Self-Attribution	0.85	0.04	Accepted
H1( )	Investment xperience to Herding	-0.04	0.70	Rejected

* Significant at 5% ** Significant at 10% *** Significant at 1%

Based on the hypotheses and results from Table 6.5, Hypotheses 2(a) is accepted, indicating that investment experience positively influences self-control bias with a statistically significant estimate of 0.85 and a p-value of 0.046. Hypotheses 2(b) is alsoaccepted, showing a negative influence on availability bias with an estimate of -

0.097 and a p-value of 0.034. Hypotheses 2(c) is rejected, as the influence on overconfidencebias is not significant (estimate 0.442, p-value 0.467). Hypotheses 2(d) is rejected, showing no significant impact on representative/familiarity bias (estimate 0.133, p-value 0.503). Hypotheses 2(e) is accepted, indicating a negative influence on loss-aversion bias (estimate -0.122, p-value 0.056).

Hypotheses 2(f) is accepted, with investment experience negatively influencing mental-accounting bias (estimate -0.296, p-value 0.000). Hypotheses 2(g) is rejected, as the influence on regret aversion bias is not significant (estimate 0.257, p-value 0.578). Hypotheses 2(h) is accepted, indicating a negative influence on anchoring bias(estimate -0.14, p-value 0.028). Hypotheses 2(i) is accepted, showing a negativeinfluence on self-attribution bias (estimate 0.85, p-value 0.042). Finally, Hypotheses 2(j) is rejected, as the influence on herding bias is not significant (estimate -0.04, p- value 0.708).

CONCLUSION

This study found the same thing that Baker et al. (2018) and Prosad et al. (2015) did: investors with more experience will be surer of their decisions than investorswithless experience. People who have invested in the stock market for a long time aresure of themselves because they know a lot about it, can pick good stocks, and are

always in charge of how well their investments do. Kaustia (2010) said that buyers give up on

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bad stocks when they want to make money and don't want to lose it.

Additionally, the outcome is connected to the research by Barber and Odean (2000). According to them, investors who are too sure of themselves tend to overestimate howaccurate their information is and how much money they can make by selling. Furthermore, they noticed that people who have experience in the stock market tendto sell about 70% of their common stock investments every year. This suggests a connection between investors' experience and trading behaviors that are based on too much trust.

As shown by Weber and Welfens (2007) and Feng and Seasholes (2005) and Dhar and Zhu (2006), trading experience lowers the Disposition effect. This is true both in repeated trading tests and after making repeated investment decisions in real stock markets. Investors who have done this before have learned to be smarter. Investors areless likely to keep a losing stock for a long time if they have learned from past mistakes (Chen et al., 2007). The outcome shows that investors' experience is linked to the representative/familiarity bias in a bad way. Investors who have done this before are smarter now. If an investor has lost money on a business for a long time, they are less likely to keep it going. It was written by Chen et al.(2007).

REFERENCES

- Malmendier, U., Pouzo, D., & Vanasco, V. (2020). Investor experiences and financial market dynamics. *Journal of Financial Economics*, *136*(3), 597-622.
- Ismiyanti, F., & Mahadwartha, P. A. (2020). Investor Experience and Expectation towards Decision-Making Process. *International Journal of Innovation, Creativity and Change*, *12*(8), 110-130.
- Gupta, S., & Bhaduri, S. N. (2019). Skin in the game–investor behavior in assetpricing, the Indian context. *Review of Behavioral Finance*, *11*(4), 373-392.
- Chen, G., Kim, K. A., Nofsinger, J. R., & Rui, O. M. (2007). Trading performance,disposition effect, overconfidence, representativeness bias, and experience of emergingmarket investors. *Journal of behavioral decisionmaking*, *20*(4), 425-451.
- Barber, B. M., & Odean, T. (2002). Online investors: do the slow die first?. *TheReview of financial studies*, *15*(2), 455-488.
- Dhar, R., & Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management science*, *52*(5), 726-740.
- Chen, G., Kim, K. A., Nofsinger, J. R., & Rui, O. M. (2007). Trading performance,disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of behavioral decision making*, *20*(4), 425-451.
- Baker, H. K., & Nofsinger, J. R. (Eds.). (2010). *Behavioral finance: investors,corporations, and markets,* John Wiley & Sons, (Vol. 6)125-134.
- Kaustia, M. (2010). Prospect theory and the disposition effect. *Journal of Financial and Quantitative Analyis*, *45*(3), 791-812.