

ARTIFICIAL INTELLIGENCE IN MANAGING EMOTIONAL BEHAVIORAL BIASES ON INVESTMENT DECISION MAKING

Kesu Singh

Assistant Professor in Commerce, Dev Samaj College for women, Panjab University,
Chandigarh

ABSTRACT

Traditional financial prospects, like Capital Asset Pricing Model (CAPM), ignore how actual people really make decisions and instead place all investment decisions in the hands of rational individuals. However, in practice, investing behaviour varies. Examining behavioral biases in investing the factor influencing the decision making by the investors is the main agenda of this study. To gather the opinions of millennial investors, a questionnaire was created and distributed. To explain the process of selecting an investment, the terms loss aversion (LA), regret aversion (RA) effect, and overconfidence (OC) bias were employed. Artificial Intelligence (AI) has emerged as a powerful tool in managing these biases and improving investment decision-making processes. AI-driven algorithms are capable of analyzing vast amounts of financial data, market sentiment, and investor behavior to identify and understand various emotional biases such as overconfidence, loss aversion, and herd mentality. The findings demonstrated that all three biases—LA, RA, and OC bias—have a significant and beneficial impact on investment decisions. According to the findings, active investors display more OC prejudice, whilst idle traders are more likely to be subject to RA and LA bias. In terms of educating customers and promoting improved decision-making, the study's findings may have significant policy implications for analysts and investment decision-makers.

Keywords: Behavioral biases, Investment decision, Emotional Biases, Artificial Intelligence

1. INTRODUCTION

Making decisions is a cognitive process that involves humans. Decision-making is described as choosing the best option from a set of possibilities using procedures (Bhatia et al., 2020). People stray from logical choices, and depending on the sort of investor, investment behaviour deviates on a varied degree. Without considering the consequences of behavioural bias, mean-variance optimization produces stereotyped investing behaviour that looks for the same ideal hazardous portfolio. The information sets that real investors have are not always the same, and even when they are, they are not usually processed in the same way. There might be a variety of probability distributions for future return rates. Second, with the given probability distribution of profits, consistently poor or inconsistent judgements are made (Babajide & Adetiloy, 2012; Toma, 2015). Whether these irrationalities lead to the stock market being inefficient is now the intriguing topic. If there are enough arbitrageurs (rational investors) who can benefit from attractive arbitrage opportunities in the market, it does not matter since their activities will return prices to their inherent value. As a result, the fate of the market depends on whether there are enough logical investors. Investment professionals can enhance economic results by better understanding behavioural biases (CFA, 2019). Black began describing ideas and kinds of noisy trading in 1986 and described them as a key element in security markets. Black, according to Trueman (1988), has not provided an explanation for the rationale for investors' speculative trading. Black (1986) popularised the "noise trading" trading strategy. According to him, exploiting noise as information must be a significant component in the trading markets. The reason why an investor would logically

decide to engage in noise trading was a topic he ignored from his discussion, though (Trueman, 1988). According to the research of De Long (1990), merchants who make unreasonable noise expect larger profits. The study briefly addresses cognitive theories that examine how circumstance and individual traits interact while making stock market investment decisions. In addition, Toma (2015) noted that biased judgements were made as a result of investors' incapacity to know for sure and anticipate market moves for the future. The skills of overconfident investors who choose to exaggerate their impact on outcomes have been questioned by Abreu (2019).

2. LITERATURE REVIEW

Researchers, economists, and psychologists have assessed how investment judgements have gone from reason for many years. Their research revealed that people do not use the anticipated utility theory as a guidance when making decisions that have a high financial reward or when following behavioural guidelines. Instead, they separate investment choices using logical accounting; as a result, an investor may run a bigger risk with just one investment account. However, the investor adopts a fairly conventional stance with a different organization dedicated to his emotional attachment. The first is how a benefit-cost assessment occurs, the second is a particular account tasks task, and the final one is the statement assessment and choice bracketing frequency. Thaler (1999) and Kahneman (2003) provided a summary of how these three rational accounting components are used by individuals in their activities. In conclusion, every component goes against the common sense accounting premise of how an economy works. Therefore, rational accounting affects the decision and has an impact on investment possibilities.

Kahneman et al. discovered in their 1991 study that speculators with loss aversion bias typically make incorrect decisions. Blavatsky and Pogrebna (2008) and Hassan et al. (2014) asserting that women are typically less risk-averse than males while investing. Loss aversion bias influences investors' decision-making in a favourable and substantial way (Lim, 2012; Khan, 2017). The results of the research by Bashir et al. (2013) are distinct from those of the earlier investigations. The loss aversion bias, he discovered had little impact on the choices made by investors. 10,000 accounts at major trading firms were examined by Odean (1999), who discovered that traders most frequently support the regret aversion. According to Muermann and Volkman's (2006) research, regret-averse investors frequently invest in defined contribution plans. Remorse aversion, according to Shefrin and Statman (1985), encourages investors to favour equities that offer regular dividends. According to research by Kengatharan and Luu (2014), investors' decision-making is positively impacted by the regret aversion bias (Lim 2012; Kengatharan, 2014; Khan 2017).

Investors that are overconfident respond excessively to market information (Odean, 1999). Men trade excessively because they are more confident than women, which reduces their profits (Barber, 2001). Daniel et al. (1998) expanded the body of knowledge by fusing self-attribution bias with overconfidence bias. He noticed that when stockholders respond to confidential information, they overconfident. Investors' earlier experiences might influence their conduct and seem as overconfidence, as shown by Zaidi and Tauni (2012).

Investors, demography, and risk tolerance are only a few of the variables that affect the extent of behavioural biases (Harikanth & Pragathi, 2012). It was examined by Zaidi and Tauni (2012) that OC bias and IT are closely associated. Additionally, it has been found that while making a decision on a short-term investment horizon, investors tend to exhibit higher behavioural biases. Additionally, behavioural biases do not exist in isolation. Instead, they support one another.

3. ARTIFICIAL INTELLIGENCE ROLE IN MANAGING EMOTIONAL BIASES

Education and Awareness: AI-powered platforms can highlight common behavioral biases like loss aversion, overconfidence, and herd behavior for investors through targeted education and awareness initiatives. Investors can become more aware of their own decision-making processes and take action to lessen the influence of these biases by studying them.

Behavioral Coaching: Real-time behavioral coaching for investors can be provided via chatbots or virtual assistants powered by AI. These assistants can serve as a reminder to investors to maintain discipline in the face of market volatility, refrain from making snap judgments based solely on feelings, and stick to their long-term investment plans.

Decision Support Tools: Artificial Intelligence has the potential to provide decision support tools that offer investors unbiased analysis and suggestions, thereby mitigating the impact of emotional biases. These tools can help investors make more logical investment decisions by combining data-driven insights and behavioral finance principles.

Personalized Recommendations: AI systems are able to examine the risk tolerance, investing objectives, and past performance of investors in order to generate customized recommendations based on each user's unique situation. AI can lessen the effects of biases like overtrading and a reluctance to diversify by taking into account each investor's individual situation.

Robo-Advisors: Robo-advisors with AI capabilities can build and oversee investing portfolios for clients based on pre-established risk profiles and goals. By automating investment choices, these tools can lessen the impact of human emotions on portfolio management.

Sentiment Analysis: AI is able to evaluate news and market sentiment to give investors a dispassionate evaluation of the state of the market. AI can assist investors in making more logical and knowledgeable judgments by sifting through media sources to remove noise and emotional cues.

Risk Management: AI systems are able to keep a close eye on investment portfolios and warn investors of any hazards posed by behavioral biases, like over-concentration in one asset class or area. AI can assist investors in avoiding costly errors caused by emotional decision-making by proactively managing risk.

4. RESEARCH METHODOLOGY

The deductive technique was applied in this research, which is founded on a positivist worldview. Real occurrences were identified experimentally and extended using logical analysis. The standard for determining the validity of any claim was whether our knowledge claims—i.e., behavioural theory predictions—corresponded to the data we gathered through our primary survey. The replies from investors in Punjab, India, were gathered via a survey-based questionnaire. This poll was intended for a group of about 348 investors. After assessing the content and face validity, the instrument was taken from the literature with a small amount of rewording. Biases in behaviour like LA, RA, and OC were taken from Lin (2011). Likert scales measuring behavioural biases ranged from severely disagreeing or 1 to strongly agreeing or 5. There were two, four, and four questions in LA, RA, and OC, respectively.

H1: The choice to invest and loss aversion are highly positively correlated.

H2: The regret aversion bias is strongly and favourably associated with investment choices.

H3: Investment decisions are considerably and favourably influenced by overconfidence bias.

5. RESULT AND DISCUSSION

Descriptive statistics were employed to examine the respondent population's demographic makeup. The five-point Likert scale was used to acquire all explanatory and explained factors. In order to elegantly observe the responder biodata, we used a demographic profile. Due to the fact that there were so few female investors in Punjab, India, men made up the majority of the responses. As a result, the majority of responders in our sample (89%) were men. Most of investors appeared young, between 20 and 29 years old, matching the age of the responders.

The participants were split between married (56% of them) and single (44%). A well-educated sample was chosen with regard to the respondents' education.

Further, Investment choice, the Loss Aversion force, Regret Aversion, and Overconfidence bias were all demonstrated in the correlation research. Significant positive correlations of 0.234, 0.228, and 0.358 were found between the investment choice and LA, RA, and OC. chi sq test was conducted to estimate the effect of Loss Aversion, Regret Aversion and Overconfidence on Investment Decision making. The p value as displayed in table 3 for effect of Loss Aversion, Regret Aversion and Overconfidence on Investment Decision making is 0.000, 0.000 and 0.000 for all three relations respectively which is less than 0.05. All of the variables have been demonstrated to significantly influence how investors make decisions

6. CONCLUSION

This study's objective was to evaluate how behavioural biases affect investors' decision-making when they choose to make an investment. Through the use of a convenient non-random sample approach, a survey was carried out utilising a questionnaire created for gathering the replies of target respondents. The outcome demonstrated how the Loss Aversion, Regret Aversion effect, and Overconfidence biases had a substantial and favourable influence on investing decisions. The findings showed that there was a significant positive association between overconfidence and the regret aversion impact as well as loss aversion on investment decisions. These results were important and added to the corpus of literature already in existence, as was experimentally clear. Only quantitative data were gathered for this investigation, and a questionnaire-based survey was used to do so. Thus, in order to gain a greater understanding these kinds of issues, future research must include an extensive variety of qualitative study approaches. Therefore, the aforementioned aspects should also be investigated in future study. It is also advised that future scholars think about doing the poll again and comparing the findings. The previous survey's results will be compared to those of upcoming ones, which will be a great addition to the literature.

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APPENDIX

I. FIGURES

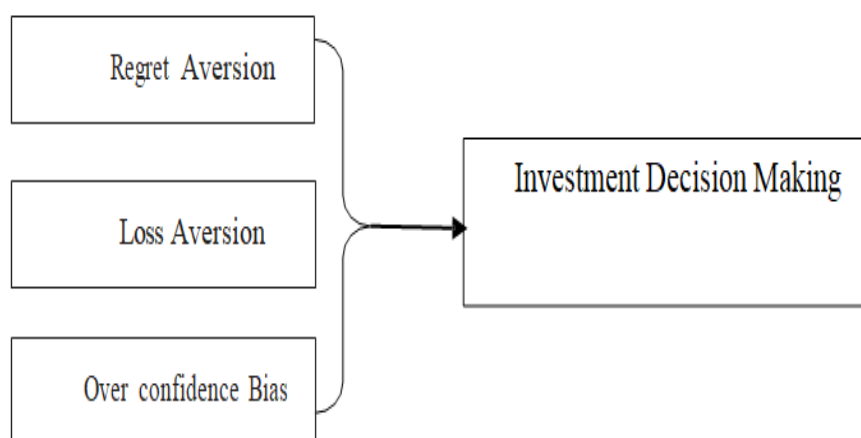


Figure1. The Theoretical Framework of the Study

II. TABLES

Table 1. Descriptive Statistics

Variable	N	Mean	Std. Deviation	Skewness	Kurtosis
Loss Aversion (LA)	348	1.8657	0.85125	-0.213	-0.395
Regret Aversion (RA)	348	2.2995	0.65895	-0.259	0.285
Overconfidence (OC)	348	2.1885	0.92356	-0.358	0.365

Source: Author's estimations

Table 2. Correlation

Variables	Investment Decision Making	LA	RA	OC
Investment Decision Making	1			
LA	0.234**	1		
RA	0.228**	0.249**	1	
OC	0.358**	0.257**	0.236**	1

Source: Author's estimations. Significance level 0.05

Table 3 Chi-Square Tests				
		Value	Df	Asymp. Sig. (2-sided)
Loss Aversion * Investment Decision making	Pearson Chi-Square	1256.325	975	.000
	Likelihood Ratio	256.325	975	0.989
	Linear-by-Linear Association	14.236	1	.000
	N of Valid Cases	348		
Regret Aversion	Pearson Chi-Square	1263.256	975	.000
	Likelihood Ratio	263.256	975	0.975
Investm	Linear-by-Linear	16.259	1	.000

ent decision making	Association			
	N of Valid Cases	348		
Overconfide nce * Investment Decision making	Pearson Chi-Square	1285.325	97 5	.000
	Likelihood Ratio	285.325	97 5	0.986
	Linear-by-Linear Association	15.485	1	.000
	N of Valid Cases	348		