

Artificial Intelligence and Investor Decision-Making: Evidence from the perspective of Behavioural Bias

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Abstract:

This paper discusses the effect of the chosen behavioural biases on the investment decisions of individual investors and explores the possibility of artificial intelligence (AI) modifying the association between the biases and investment decisions. The research is based on primary data on 462 individual investors in India that investigates the study by a structured questionnaire and makes use of the Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.0. Reliability, convergent validity, and discriminant validity were determined and the importance of structural relationships and moderating effects were also tested through bootstrapping with 5,000 resamples.

The results indicate that anchoring bias, representativeness bias, loss aversion bias, overconfidence bias, and herding behaviour have a significant impact on the decision making of investors. The use of AI was observed to moderate the association between anchoring bias and the herding behaviour with the investment decisions, and no significant moderation was reported with the representativeness bias, overconfidence bias, and the loss aversion bias. The research provides insights into behavioural finance and fintech literature by pinpointing the behavioural biases that could/could not be reduced by the adoption of AI, providing empirical data in an up-and-coming market environment and valuable insights into the financial institution and fintech portal.

Keywords *Artificial intelligence, Behavioural biases, Investment decision-making, Anchoring bias, Herding behaviour, India*

Introduction

Artificial intelligence plays a very important role in every domain, be it Marketing strategies, Finance or Investment decisions (Ameen et al., 2023). AI has helped making decision making simple, where humans get stuck in emotions and are not able to take rational decisions at times (Shanmuganathan, 2020). The integration of AI in Finance has completely changed the way decisions are taken (Rohner, 2021). The decisions are now more rational and do not have human emotions intervention in it (Sandhu et al., 2024). Decisions of humans are often influenced by emotions and they tend to make errors or wrong decisions because of it (Jain et al., 2023). During the times of high fluctuations and uncertainties, this tendency making errors multiplies (Costa et al., 2019). This leads to even more financial risk and losses as the decision they assume to be rational and data based, is actually not (Fama, 1970). For example, “Hindsight Bias” is where people believe they already knew what was going to happen, when it has already happened. Like if the market fell, some people assume they already knew it will fall. This was the reason it was very crucial to develop this new field of finance, known as behavioural finance of rational decision making (Shefrin, 2002).

Now as AI is very easily available in various forms, that help us to take rational decisions, it is the need of an hour to integrate it with financial decision making (Yadav et al., 2025). These platforms do not involve human intervention in making financial decisions (Belanche et al., 2019). As the markets and the new evolving products have now become so complex, investors tend to seek guidance, to get better results (Hans et al., 2024), this guidance was restricted to humans until AI was introduced (Leone et al., 2021). Now AI can be used to make investment decisions at a very economic spend and at ease (Asere, 2024).

There are quite a few studies which help us understand the impact of behavioral and emotional biases on investment decisions (Kapoor and Khare, 2024), but studies on how AI can be used to take the investment decision which help us mitigate the behavioral biases is rare (Samantaray and Maheshwari, 2025). This study focuses on understanding the role of AI to help the investors take investment decisions which are rational, ie, does not involve emotional biases.

This study focuses on and will try to answer the following two questions:

Does behavioral biasness affect the way a person takes investment decisions?

Will using AI for investment decisions help mitigate from such behavioral biases?

The result of this study will help the financial firms to understand about how developing an AI can help their clients take rational investment decisions.

Review of Literature

Because of behavioral biasness, people tend to take quick decisions, using their own instincts, without going into detail of the problem. Many a times which leads to disheartening and poor results (Charles, 2015). When we focus on the biases from investment point of view, there are five biases which can impact the investment decisions (Maheshwari, 2025). First, “Anchoring” is when people stick to a particular situation and take its reference to estimate the result of another situation, when both the situations are independent of each other. Second is “Overconfidence”, where they assume they have complete knowledge of what is happening and why, and their prediction is not going to fail. Third is “Representative Bias”, where while investing, people tend to make patterns and link one event is the cause of another, when there actually is not causal relationship. Fourth is “Loss aversion”, which is the fear of the loss. It was observed that the fear of loss is much greater than the happiness of the gain. This many a times also leads to inactivity (Levy, 1992). Fifth is “Herd mentality” is following the crowd, without knowing the reason behind it.

In recent few years, AI is being used in many different areas, specially post COVID 19, which has led to better analysis of the qualitative and quantitative aspects of the economy (Shahzad et al, 2023). AI can be used now to analyse different type of financial data which will lead to better financial result (Yousaf, 2023). AI can easily identify trends in the data provided and can predict the probability of occurrence of different events in the future (Jariwala, 2025). It can also analyse the past price data and can predict the future stock and commodity prices (Rana, 2023).

Anchoring bias is when an investor relies too much on the previous information, and try to judge the next event with the previous one, even when they are independent (Shin and Park, 2018). Thus, this bias may affect the way an investor takes investment decisions (Kleine et al., 2022). With this, the first hypothesis can be framed as:

H₁ - Anchoring bias significantly affect the Investment Decision of an investor.

The proposed study conceptual framework and the hypothesised relationships are shown in Exhibit 1.

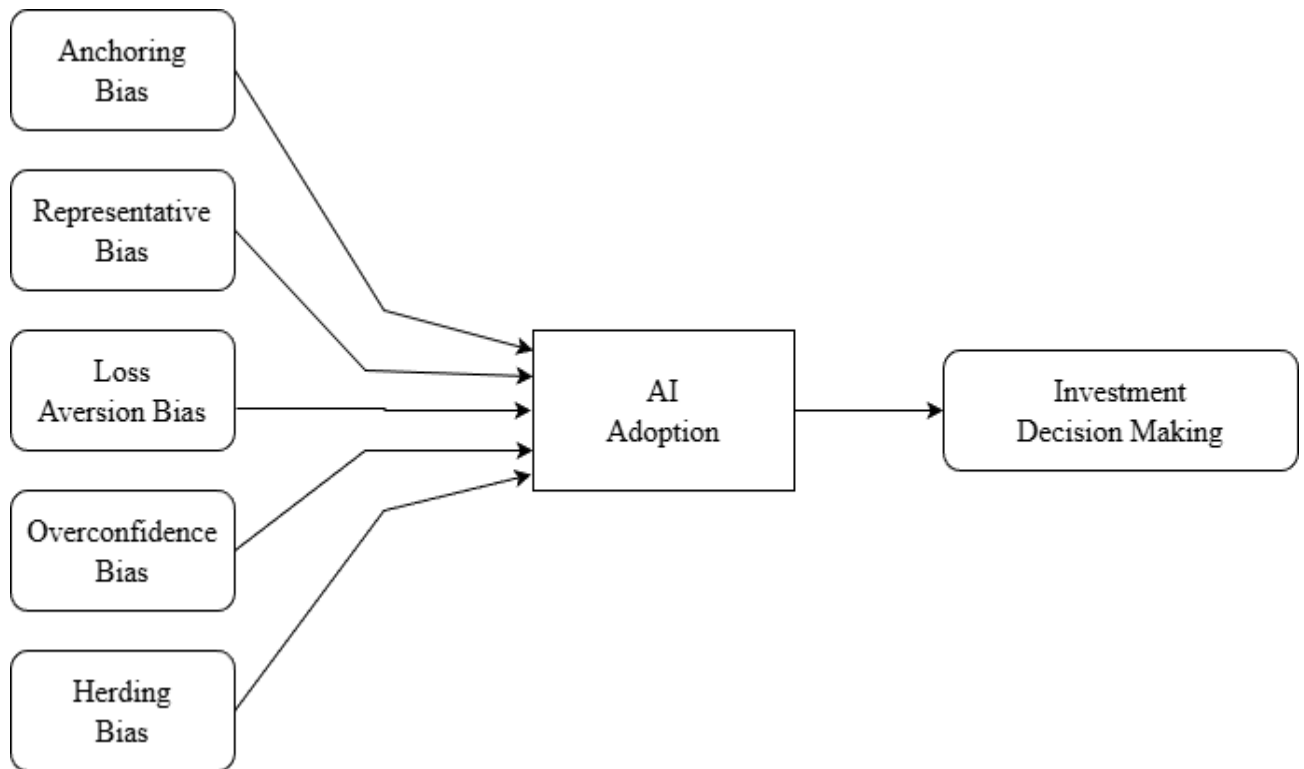


Exhibit 1. Conceptual framework proposed in the study

Source: Author's drawing

Representative Bias is forming a relation of an event with a cause, even when there's no relation in them (Adiputra, 2021). Say after tossing the coin 4 times, it resulted into alternative heads and tails in form of H, T, H, T. Now a person can form a pattern in it and can presume that as per the trend, on next toss, there's very high probability of a Heads (Shah et al., 2018). Though the actual probability of a Heads or Tails is still 50-50. This brings us to the second hypothesis:

H₂ - Representative Bias significantly affect the Investment Decision of an investor.

Loss Aversion Bias is when an investor is afraid of making loss in the trade and backs off. This often leads to inactivity of the investor (Kahneman and Tversky, 1979). It is believed that loss bring more

grieve than happiness the same amount of profit brings (Barberis et al., 2003). This fear is believed to impact the investment decision.

H₃ - Loss Aversion bias significantly affect the Investment Decision of an investor.

Overconfidence is when an investor overestimates his potential to analyse the market. He starts to assume that he can predict the next movement of the market very easily (Odean, 2001). In the process, they underestimate the risk in the investment which may lead to big losses. As per Bijulal (2024), this bias leads to Gambler's Fallacy. With this, we draft our next hypothesis:

H₄ - Overconfidence bias significantly affect the Investment Decision of an investor.

People often invest in different companies just because their friends or colleagues are investing in the same, without doing any research about the company. This is known as Herd Behaviour (Gonzalez, 2020). It has cascading effect, as if one makes mistake, all the people following that person suffer.

H₅ - Herd Behaviour significantly affect the Investment Decision of an investor.

The early works of Tversky and Kahneman (1974) in behavioral finance demonstrated that cognitive biases play a major role in human decision-making and that to a certain extent people rely on their heuristics which might result in the decision to invest in the wrong way. Such over-reliance on cognitive biases can give rise to poor investments. In addition to this, Hasan et al. (2022) explain anchoring bias as a phenomenon through which loss of an investor's touch with the best investment outcomes occurs as a result of irrational information interpretation and application, which is primarily caused by the investor's biased reliance on the information. This paper is an extension of these biases, investigating whether the use of artificial intelligence tools would be able to lessen their influence in the course of investment decision-making.

H₆ - Anchoring bias can be mitigated using Artificial Intelligence while making an Investment Decision

Representative bias, which can be regarded as a type of belief perseverance, comes into play when individuals resort to mental shortcuts, thereby making the decision very fast and easy (Ahmad & Wu, 2024; Hasan et al., 2022). In this way, investors tend to put a lot of emphasis on one outstanding characteristic—like historical performance—and overlook other relevant facts that could have an impact on the outcome (Hirshleifer, 2001). This restricted perception can lead not only to wrong direction but also to the draining of investors' money. A classic case of this bias is when investors think that stocks of companies with great historical performance will always be good in the future instead of fairly considering the market shifts and company-specific risks. The application of Artificial Intelligence (AI) could be a remedy because it permits analyzing multiple facets of a decision at once, thus reducing the necessity for oversimplified mental images and increasing the support for informed and possibly profitable investment choices.

H₇ - Representative Bias can be mitigated using Artificial Intelligence while making an Investment Decision

Some previous studies has shown that overconfidence bias has a major impact on investor behavior and may also be one of the causes of the market inefficiencies. For example, Alp Coşkun et al. (2023) illustrated how overconfidence was a common trait among the investors in the Borsa Istanbul market and how it distorted decision-making and increased market instability. In this regard, the use of artificial intelligence might be a suitable method to moderate the situation since AI would minimize the use of subjective judgment which is usually the cause of overconfidence (Sunstein, 2019). AI is not like human decision-makers who rely on their intuition; rather, AI systems can analyze huge quantities of financial data in an unbiased and systematic manner and thus arrive at more balanced decisions. Furthermore, AI-based tools have the ability to spot market trends and motive inconsistencies that may not be so obvious to the lone investor. The application of AI in finance can allow for the comparison between investors' predictions and realized outcomes, thus providing feedback that

illuminates the difference between what was expected and what actually happened (Ding, 2024). Such feedback promotes the contemplation of the past choices, increases the awareness of one's self, and trains the investor to be more confident but not overconfident. Overall, these features help to support the argument that the use of AI in investment decision-making will reduce the influence of overconfidence bias.

H₈ - Overconfidence bias can be mitigated using Artificial Intelligence while making an Investment Decision

Loss aversion bias is a psychological phenomenon that alters the viewpoint of an individual in a way that he/she puts more emphasis on losses than on gains, thereby neglecting any other effects in comparison with the latter; this phenomenon is a major basis of prospect theory (Kahneman & Tversky, 1984). Previous studies have confirmed this bias as a major factor even in the case of investing through tech aided means. For instance, Bhatia et al. (2020) found out that investors are still showing loss-averse behavior while using the AI-based robo-advisory platforms mainly because of their limited trust in the automated decision-making systems, which in turn restrict their ability to completely overcome the bias. On the other hand, Kleine et al. (2022) observed that loss-averse tendencies are not the exclusive preserve of real-world investors but also exist in narratives where characters from popular media, like those in movies and dramas, keep making the wrong choices because of their fear of losses. This not only advocates the argument that narratives are powerful influencers of economic behavior and decision patterns (Shiller, 2017) but also the fact that investors' fear of losses might lead them to sell off their shares in times of bear markets thus prolonging the market's downtrend. They tend to sell their shares when they think the market is at its worst and by so doing force the market down even further. Artificial Intelligence technologies at this point can step in to be a solution to this problem. It can provide objective and data-based assessments that bring about the cessation of the investment decision process driven by emotions like loss aversion and, instead, lead to more rational investment decisions.

H₉ - Loss Aversion bias can be mitigated using Artificial Intelligence while making an Investment Decision

Herding bias is a psychological inclination of the people to make their investments or financial decisions by looking and following others, rather than on personal analysis. However, the herd behavior is usually backed by peer pressure along with the information flow through social and digital media (Maheshwari & Samantaray, 2025). According to the empirical findings, herding is one of the major effects in behavioral terms that are affecting investors, while the influence is especially strong during times of high market uncertainty and volatility (Raj, 2025; Shantha, 2019). This type of decision-making can be seen most clearly in the case of the Indian stock market, which is still an emerging market. Here, the investors may perceive safety in following the majority, while at the same time, there is a possibility of irrational outcomes. Besides, the behavior of the investors to a large extent has been associated with the occurrences of market fluctuations and pricing anomalies (Suresh, 2024). However, artificial intelligence can take up a moderating role by providing personalized, data-driven investment insights that promote individual judgment (Jung et al., 2018). In this way, the tools for AI-assisted decision-making can lower the impact of herding bias on the investment process by decreasing the dependency on crowd behavior and eliminating groupthink.

H₁₀ - Herd Behaviour can be mitigated using Artificial Intelligence while making an Investment Decision

Methodology

Sampling

In this study, the sampling was done through convenience and snowball methods. 462 valid responses were considered in the study. Among the people who responded, there are 238 males (51.5%) and 224

are females (48.5%). This study uses SEM (Structural Equation Modelling) to understand the causal relationship between the variables. Exhibit 2 shows the demographic characteristics of the respondents with a summary of the distribution of gender, age, income, and investments.

Exhibit 2. Participant Demographics

<i>Category</i>	<i>Classification</i>	<i>Frequency Percentage (%)</i>	
Gender	Male	238	51.5
	Female	224	48.5
Age Bracket (in years)	18–25	162	35.1
	25–30	127	27.5
	30–40	98	21.2
	40–50	47	10.2
	Above 50	28	6.1
Annual Income (Rs)	Less than Rs 3 Lakhs	149	32.3
	Rs 3 Lakhs to Rs 5 Lakhs	138	29.9
	Rs 5 Lakhs to Rs 10 Lakhs	115	25.0
	More than Rs 10 Lakhs	60	13.0
Investment Experience	Less than 3 Years	159	34.4
	3 Years to 5 Years	141	30.5
	5 Years to 10 Years	97	21.0
	More than 10 Years	65	14.1

Source : Primary Data

Scale

A questionnaire was prepared to understand the behavioral biases and how the AI is used and incorporated by different investors in their investment journey to make investment decisions. The variables include over-confidence bias (where the investors believe they have superior skills and what they actually have and they feel that they have control over the output generated), herd behavior (where the investors get influenced and carried away by the thoughts and trading decisions of the other investors, without doing their own research), loss aversion bias (people usually fear twice as much as loosing than the happiness they get from winning the trade), representative bias (where the investor instead of focusing on statistical research, focus more on their belief and existing mental stereotype), and anchoring bias (relying more on the recent events and data, ignoring the past data).

The study aimed to understand if people prefer AI to enhance their investment decisions and if people prefer AI softwares over human advisors to reduce the behavioral biases.

Analysis

The study used SMART-PLS 4 to analyze the data collected during the research following the structural equation model (SEM) approach. This is an effective method which is often used in modeling complex variables and their relationships using the partial least square (PLS) method (Chin, 1998; Dijkstra & Henseler, 2015). The consistency of the measurement (outer) and structural (inner) model was checked and were found sufficient. To test for CMB (common method bias) in the study, the Harman's test (single factor) was employed. The study identified that using CMB was not a problem and proved to be a good tool to use as the factor (which should be below 50%) only explained 21% of the variance. The VIF (Variance Inflation Factor) was also measured in the study, which was found to be less than 3, using this it was made sure that multi-collinearity was also absent in the data (Kock et al., 2021).

Results

Measurement Model Assessment

Some factor analysis based tests like convergent validity, discriminant validity and composite reliability were used to measure the empirical support of the outer model (Hair et al., 2021; Sarstedt et al., 2020). The seven constructs used in the study are Anchoring Bias (AB), Herding Bias (HB), Loss Aversion Bias (LAB), Overconfidence Bias (OCB), Representative Bias (RB), AI Adoption (AIA), and Investment Decision (ID). These constructs have high internal consistency as indicated by the Cronbach's alpha and Henseler's rho values which were found to be above 0.7 (Sarstedt et al., 2021).

The reliability summary of the model is showcased in the Table 2. To confirm the validity of the discriminant, the study involved the use of Fornell Larcker criterion. It signifies that the square root of each construct of the average variance extracted was higher than correlation among the latent variables. The Heterotrait–Monotrait (HTMT) ratio test confirmed the discriminant validity. Exhibit 4 displays its overview, where it produced the results less than 0.85. The statistics of reliability and convergent validity of the constructs are reported in Exhibit 3. All the Cronbachs alpha, composite reliability (CR) and rhoA are greater than the recommended value of 0.70.

Exhibit 3. Reliability Summary

Latent Variables	Cronbach's alpha (α)	CR Index	ρA	Avg Var Ex
Anchoring Bias	0.794	0.876	0.801	0.709
Herding Bias	0.882	0.917	0.889	0.693
AI Adoption	0.763	0.854	0.779	0.584
Investment Decision	0.802	0.868	0.809	0.562
Loss Aversion Bias	0.829	0.884	0.833	0.637
Overconfidence Bias	0.823	0.892	0.821	0.719
Representative Bias	0.833	0.887	0.836	0.661

Source(s): Findings from the Author's study

The HTMT ratio and Fornell-Larcker criterion were used to measure the discriminant validity. Table 3 illustrates that all HTMTs are less than 0.85, which indicates that the discriminant validity is fine.

Exhibit 4. Assessment of Discriminant Validity

(a) Heterotrait–Monotrait Ratio (HTMT)

Construct	Anchoring Bias	Herding Bias	AI Adoption	Investment Decision	Loss Aversion Bias	Overconfidence Bias	Representative Bias
Anchoring Bias							
Herding Bias	0.142						
AI Adoption	0.392	0.115					
Investment Decision	0.648	0.328	0.249				
Loss Aversion Bias	0.093	0.347	0.127	0.228			
Overconfidence Bias	0.355	0.081	0.284	0.204	0.061		
Representative Bias	0.166	0.31	0.152	0.421	0.219	0.097	

Source(s): Findings from the Author's study

(b) Fornell–Larcker Criterion

Construct	Anchoring Bias	Herding Bias	AI Adoption	Investment Decision	Loss Aversion Bias	Overconfidence Bias	Representative Bias
Anchoring Bias	0.842						
Herding Bias	0.069	0.833					
AI Adoption	0.318	0.057	0.766				
Investment Decision	0.517	0.281	0.193	0.752			
Loss Aversion Bias	0.332	0.301	0.249	0.187	0.796		
Overconfidence Bias	0.298	0.053	0.239	0.164	0.039	0.846	
Representative Bias	0.118	0.266	0.177	0.339	0.196	0.012	0.818

Source(s): Findings from the Author's study

Structural Model Assessment

Once the measurement model was validated, the structural model was used in the study to identify the relationship between the latent variables (Figure 2). The bootstrapping method was then used where the original sample was repeatedly redrawn 5000 times which in turn evaluated the significance and robustness of the path (Richter et al., 2023). The predictive ability of the model was estimated using the R^2 values while the F^2 statistics were used to quantify the impact of each predictor. The investment decision (ID) which is a dependent variable was found to have the R^2 value of 0.512 and the adjusted R^2 of 0.489, which shows moderate explanatory ability. The study also showed that there was a statistically significant effect of Anchoring Bias (AB) on ID, as it had a F^2 value of 0.447 which indicated high impact. Similarly, ID was also positively affected by representative bias (RB) but to a minor extent denoted by F^2 value of 0.073. The study also indicated that the AI adoption (AIA) was a moderator in the relationship of anchoring bias and investment decision, though the F^2 value of 0.12 indicated that the size of the effect was very small. The AI adoption also moderate the relationship of herding bias (HB) and ID which was indicated with the F^2 value of 0.039 signifying a small influence. As per the study done by Sarstedt et al. (2020), the F^2 values of 0.02, 0.15, and 0.35 denote small, medium, and large effects, respectively. The table 4 shows the summary of all the hypothesis testing.

The H_1 was found to be statistically significant showing the significant impact of Anchoring Bias on ID ($\beta = 0.540$; $t = 10.453$; $p < 0.01$). A direct positive relationship and statistically significant impact was also found while testing H_2 for representative bias on ID ($\beta = 0.188$; $t = 3.512$). Loss aversion bias (LAB) and ID ($\beta = 0.169$; $t = 1.742$) also showed positive and significant relationship supporting H_3 . The H_4 was tested for Overconfidence Bias (OCB) which was supported ID ($\beta = 0.082$; $t = 1.742$; $p < 0.10$). The

H₅ was then tested for Herd Behavior on the ID and the relationship found was positive ($\beta = 0.091$; $t = 2.169$). The estimation of the structural model described in Exhibit 5 is done through PLS-SEM.

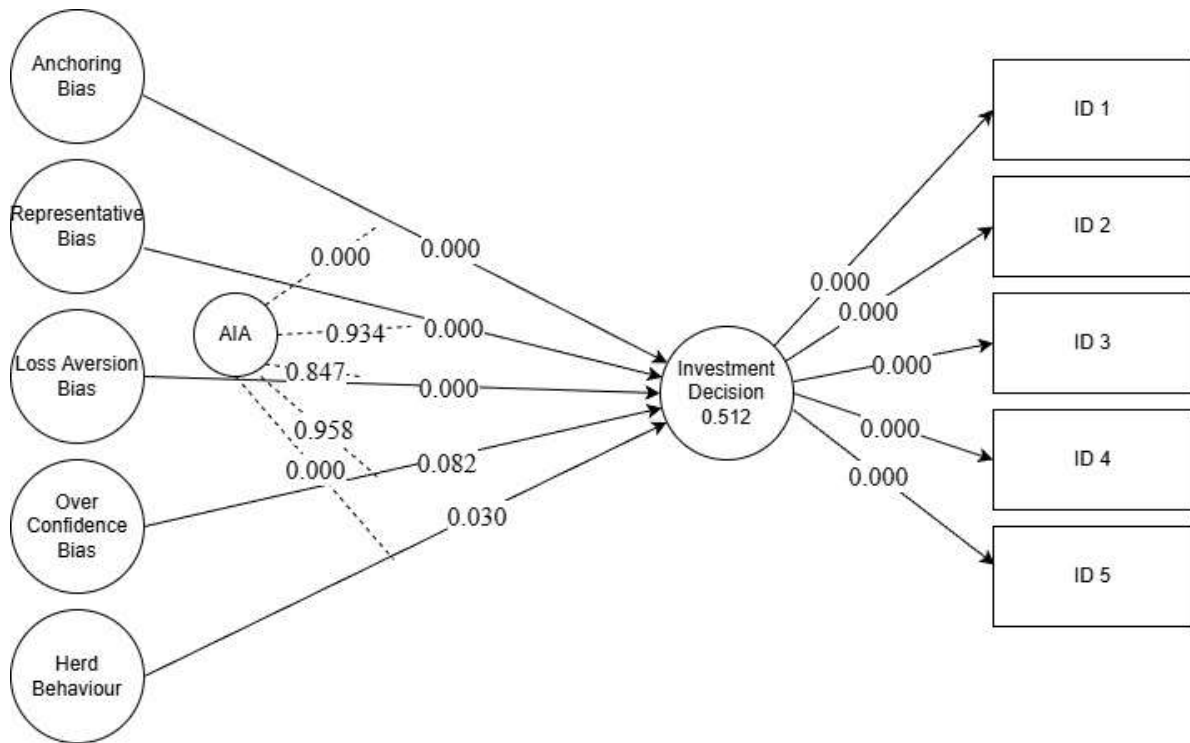


Exhibit 5. SEM flowchart

Source: As per the Empirical study outcomes

After testing the direct relationship of all the biases on the investment decisions of an investor, the adoption of AI as moderator was investigated. The further hypotheses H₆ and H₁₀ found that there exist a strong impact of AI adoption on the relationships between AB and ID, and HB and ID, respectively, with $p < 0.01$. The remaining hypotheses H₇ to H₉ on the other side suggested that there is no significant moderating effect of AI adoption on the effect of biases like OCB, RB and LAB in making investment decisions. The structural path coefficients, test statistics and the hypothesis test results are summarised in Exhibit 6.

Exhibit 6. Structural Path Estimates and Hypothesis Results

Hypothesis	Structural Path	Beta (β)	Standard Error	Test Statistic (t)	Probability Value	Significance Threshold	Hypothesis Outcome
Hypothesis 1	Anchoring Bias $\rightarrow$ ID	0.540	0.052	10.453	0.000	< 0.01	Empirically Accepted
Hypothesis 2	Repres. Bias - ID	0.188	0.054	3.512	0.000	< 0.01	Empirically Accepted
Hypothesis 3	Loss Av. Bias - ID	0.169	0.046	3.782	0.000	< 0.01	Empirically Accepted
Hypothesis 4	Over Conf Bias - ID	0.082	0.044	1.742	0.082	< 0.10	Empirically Accepted
Hypothesis 5	Herd Behav - ID	0.091	0.042	2.169	0.030	< 0.05	Empirically Accepted
Hypothesis 6	AI Adoption $\times$ AB - ID	0.221	0.044	5.078	0.000	< 0.01	Empirically Accepted
Hypothesis 7	AI Adoption $\times$ RB - ID	0.005	0.058	0.083	0.934	Statistically Insignificant	Empirically Rejected
Hypothesis 8	AI Adoption $\times$ OCB-ID	0.003	0.040	0.052	0.958	Statistically Insignificant	Empirically Rejected
Hypothesis 9	AI Adoption $\times$ LAB-ID	0.010	0.048	0.193	0.847	Statistically Insignificant	Empirically Rejected
Hypothesis 10	AI Adoption $\times$ HB - ID	0.149	0.041	3.615	0.000	< 0.01	Empirically Accepted

Source(s): Findings from the Author's study

Discussion and contribution

The study was divided into 2 parts, the first part talked about the direct relationships of the behavioral biases like Herding Bias (HB), Representative Bias (RB), Anchoring Bias (AB), Overconfidence Bias (OCB) and Loss Aversion Bias (LAB) on the investment decision (ID) taken by the individual investors in India. In the subsequent part, the study tried to find out if AI adoption lead to moderation in the relationship of these biases and the investment decisions. It was found in the current study that all the 5 five biases influence the investment decisions.

Some previous research had the same result as our empirical study pointing out that Anchoring Bias has significant influence on the investment decisions (Owusu & Laryea, 2023), whereas, some literature like Madaan and Singh (2019) do not agree to it.

The current study also found that Representative Bias significantly impact the investors decisions, indicating that they focus more on the past data, ignoring the current economic and sectoral information and data (Adiputra, 2021). The study also revealed that the investors that are

overconfident about their judgements, decisions and theories showing OCB also significantly affect their investment decisions (Ayaa et al., 2022; Raj, 2025; Rashid et al., 2022).

Loss aversions bias makes investors more conservative while taking an investment decision and force them to take safer investment options. Herding Bias is also observed in investors in various situations when they themselves are unable to take any decisions specially in some crisis like situations such as Covid 19 (Mittal, 2022; Jain et al., 2020).

The involvement of AI Adoption while taking the investment decision was then analyzed further in the study. The further tests show that the Adoption of AI did not significantly affect the Representative bias, Loss Aversion Bias and Over-Confidence Bias while taking any investment decision (Bhatia et al., 2021; Maheshwari & Samantaray, 2025). For example, even after the involvement of AI, it was observed that the recent news has greater impact on the share prices, which is same as the people with representative biasness.

On the other hand, the adoption of AI moderated the behavioral biases like Anchoring bias and Herd bias, reducing its impact while taking the investment decisions. This result supported the previous studies like Echterhoff et al. (2022) and Asim et al. (2023) which mentioned that AI models reduce the impact of such biases during uncertainties and high market fluctuations like during Covid-19.

Implications

This research was conducted to understand if AI adoption moderate or alter the relationship between behavioural biases and investment decisions taken by an investor. The outcome of the study is useful for all the participants of the financial market as it emphasizes on the use of AI to help the investors take rational financial decisions. A large number of investors stay away from the market as they are afraid of losses due to their behaviour biases. This research will give them a solution to this problem they can now invest using AI decision making.

The current study identified that AI adoption reduced the Anchoring Bias (AB) and Herding Bias (HB) impact on the decisions taken by an investor while investing. This proved the importance of AI and its ability to eliminate the human-like biasness from the trading decisions. But AI could not eliminate the biases like Representative Bias (RB), Overconfidence Bias (OCB), and Loss Aversion Bias (LAB) proving even AI intervention will have some human-like biases while taking the investment decisions. Eliminating the emotional biases from trading and investment decisions has now become tough even though emotions are not expected from a machine.

Hence, further improvement in the AI model is required which can eliminate a wider range of emotional biases while taking the investment decisions. In addition to the use of AI in moderating the investment decisions, the policy formation for ethical and transparent use of AI is also required by SEBI. The investment is expected to become easy and more sustainable with such a regulatory framework.

Conclusion and Directions for Future Research

This research paper does a thorough analysis on how the behavioral biases impact the financial decision taken by an investor. The study also finds that the AI's adoption can reduce the emotional biases' impact but cannot completely eliminate the effect of human emotional biases as the market prices is driven by the combined decisions of all the investors which is mostly driven by emotions and news. It was also found that the use of AI's adoption can reduce the behavioral biases' impact like anchoring and herding while taking the investment decisions, but it is not effective to eliminate all the behavioral biases.

This research was conducted in India, and hence this is the limitation that the results might be less applicable to other countries. Further research is required to cover more sample from other countries

also to add value to the study. Further studies could also include more moderating variables like financial literacy and age or sex to learn more about the behavior of investors. This research focused only on certain biases which were anchoring, representativeness, overconfidence, loss aversion, and herding bias but by considering a greater number of bias and in different social and cultural locations, one would get much better insight and this would strengthen the findings and result of the study.

Ethical statement

The primary data used in the study is developed in questionnaire survey done with individual investors. All the respondents participated in the study on a voluntary basis and informed consent was signed at the time of data collection. The study did not gather any personally identifiable data and the anonymity and confidentiality of respondents were achieved during the course of the study. No clinical trials, animal test studies, or sensitive personal information were involved in the study and hence no formal institutional ethical approval was necessary.

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Data availability

Data will be made available on request.

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Appendix

Measurement of study variables

Anchoring Bias (AB)

AB1: To what extent do your recent market experiences influence your current trading decisions?

AB2: Do you treat the original purchase price of a stock as a benchmark when making trading decisions?

AB3: When deciding whether to sell a stock, do you refer back to the price at which it was purchased?

AB4: Do you rely on recent stock price movements to predict future price changes?

Representativeness Bias (RB)

RB1: Do you tend to invest in stocks that have performed well recently while avoiding those with weak recent performance?

RB2: Do you base your investment choices on observed market trends or patterns?

RB3: Do you refrain from investing in companies that have shown poor earnings performance in the past?

RB4: Do you show a preference for investing in stocks that are familiar to you?

RB5: If a thoroughly researched stock underperforms your expectations, do you continue holding it?

Loss Aversion Bias (LAB)

LAB1: Do you believe that the discomfort from financial losses is not completely compensated by the satisfaction from equivalent gains?

LAB2: Does the emotional impact of losing money outweigh the pleasure of gaining the same amount?

LAB3: Are you more likely to hold on to losing stocks while quickly selling stocks that have gained value?

LAB4: Do significant losses remain in your memory longer than significant gains?

Overconfidence Bias (OCB)

OCB1: Do you believe your investment decision-making ability is superior to that of other investors?

OCB2: Do you feel capable of influencing investment outcomes to align with your objectives?

OCB3: Do you attribute your past investment success primarily to your own skills and expertise?

OCB4: Do you consider yourself to have comprehensive knowledge of financial markets?

OCB5: Are you confident that you outperform others when selecting individual stocks?

Herding Bias (HB)

HB1: Do the stock choices of your peers influence your own stock selection decisions?

HB2: Are you affected by your peers' decisions regarding the quantity or scale of stock investments?

HB3: Do you tend to adjust your investment decisions based on changes made by your peer group?

HB4: Do investment tips from peers, financial advisors, or media sources significantly affect your stock choices?

HB5: When negative market news emerges, do you prefer to exit stock investments and move funds into safer alternatives?

Artificial Intelligence Adoption (AIA)

AIA1: Do you plan to use AI-based tools to support your stock market investment decisions?

AIA2: Do you actively use AI-enabled technologies when making stock investment decisions?

AIA3: Would you prefer AI-driven investment services over advice from human financial advisors?

AIA4: Do you believe that using AI in investment decisions improves transparency?

AIA5: Do you believe AI adoption in investing helps reduce human judgment errors?

Investment Decision-Making (ID)

ID1: Do statements made by government authorities about a company influence your investment decisions?

ID2: Have the returns from your recent stock investments met your expectations?

ID3: Does market uncertainty discourage you from investing in stocks?

ID4: Do you evaluate a company's historical stock performance before investing?

ID5: Would you recommend stock market investing to your friends or family members?