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Role of Artificial Intelligence (AI) in Strengthening Impact of Behavioral Factors on Investment Decision Process of IT/ITES Employee Towards Behavioral Finance

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Abstract. The investment decision process of an investor involves collecting related information, analyzing the data, and making choices. The transformative power of artificial intelligence (AI) has changed various sectors, including finance, by completely improving investment analysis and prediction. This study tells the factors that influence the investment decision-making of IT/ITES employees toward behavioral finance using AI. We conducted a survey of 142 IT/ITES employees in Chennai. The research explains how artificial intelligence (AI) modifies the influence of behavior factors (BF), including heuristics, market variables, and herding effects, on the process of making investment decisions as assessed by CFA and SEM. Based on behavioral finance, the results show that behavior factors (BF) have a beneficial impact on IT/ITES personnel' investment decision process (IDP). Consequently, by using AI-driven tools and approaches, heuristics, herding effects, and market variables play important role in making informed judgments, thereby altering investment outcomes. This study gives deeper understanding of how AI enhances and increases operational insights for money fund managers, academics, stockbrokers, and investment advisors. These studies examine how AI changes or modifies the impact of behavioral factors such as overconfidence, loss aversion, while it combines AI and behavioral finance. Going along with the crowd when it comes to IT/ITES employees' investment decisions, which are important for investors' investment decisions.

Keywords. Artificial Intelligence, Behavioral Finance, Herding Effect, Heuristics, Market Variables, Investment Decision- Making (IDM).

INTRODUCTION

The advanced technology has a major impact on financial markets, by integrating Artificial Intelligence (AI) into investment decision-making process [4]. Behavioral finance, a field of study that analysis the effects of psychological factors on investors' decision-making, has accumulates major interest in recent times. IT/ITES professionals mostly depend on AI-powered solutions to make investment decisions because of their technological investments. This research explores the combination of AI and behavioral finance, investigating how AI changes or modifies the influence of behavioral characteristics. Such as overconfidence, loss aversion, and large group, on the investment choices made by IT/ITES professionals. A complete understanding of this correlation is essential to design more efficient financial strategies. Which used to consider human behavior and technical progress. The foundation of behavioral finance is the understanding of the impact of behavior by financial analysts and investors [3]. It is research on the influence of investors' behavior on their decision to invest in financial-related investments. The regulation of behavioral finance has seen a remarkable boom over the past half-century. Investors have investigated the effect of financial decisions on behavioral investments [3]. Behavioral economics describes how economics and psychology blend to explain financial mediators' decision-making (DM) techniques. Psychology examines many aspects of human behavior [9]. Also, human behavior explains how human behavior turns from common economic guesses. Human biases can be divided into four categories: heuristic, market, prospect, and herding factors.

Investment decisions involve determining which assets are safe, when, how much to allocate, and how long to maintain the investment. Different investment choices carry varying return and risk profiles, and investors may have opportunities to invest in stocks, marketable bonds, and other securities. The investment decision-making process is

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inherently cognitive and complex, differing significantly from one investor to another. Research into the underlying factors influencing individual investment decisions reveals that this process has evolved substantially over the past few decades. Investors have developed various techniques, tools, and models to guide them in making knowledgeable decisions. As they need to fully account for individual investors' unique investment behaviors and contexts, applying these complicated methods is imperfect the incorporation of Artificial Intelligence (AI) into the process of making financial decisions is changing the way investors make judgments. AI has the potential to significantly reduce the time and cost of making complex decisions by manipulating heuristic variables and advanced algorithms. For example, prospect theory indicates that when a stock's price moves after purchase, the probability of selling it drops. These patterns can be analyzed by AI systems, giving investors access to previously unobtainable information [15]. Moreover, AI can analyze stock market data to predict trends and identify abnormalities that might influence investor behavior. They noted that stock market transactions significantly impact depositors, attracting their attention and affecting overall investment performance. The ability of AI to transform investing decisions is evidence of the investment industry's progressive spirit.

Stock markets play a major role in creating investor decisions in India, which can influence the broader economy. It is most importance to identify and understand the factors that drive investment decisions in the Indian stock market. Especially as AI begins to play a more important role in this process. Depositors can get good returns by recognizing common behaviors and integrating AI-driven insights. Therefore, this study seeks to explore the impact of behavioral finance, increase by AI, on the investment decision process (IDP) of IT/ITES employees. It also focuses on understanding how these factors shape behavioral finance in the Indian market. This strengthens on understanding the ongoing factors of investment decisions is major for keeping the audience engaged and interested in the research.

REVIEW OF LITERATURE

The decision-making (DM) process, mainly based on environmental and situational variables. It has been linked to complex psychological behaviors, including those seen in psychopaths. DM is fundamental critical mental activity influenced by the decision-maker's behavior. DM evaluates by collecting relevant data and selecting the most suitable option. In the surrounding of investment, the psychological behavior of investors plays a important role in the DM process. Psychological behavior can be defined as the exchange of financial and psychological factors that influence decision-making. Behavioral finance is a field that examines and search to understand investor behavior using psychological principles, particularly in investment and stock market DM.

Artificial Intelligence (AI) has combined with behavioral finance, providing new insights into investor behavior and developing the DM process [6]. From an AI point of view, modern finance is about analysing possibilities logically and recognizing and correcting the cognitive and emotional biases that affect investment choices. AI can analyze large amounts of data, identify patterns, and predict market abnormalities by understanding investor psychology, allowing fund managers to make more informed choices. This method is different from traditional finance, which frequently relies on depositors' logical evaluation. Modern finance, supported by AI, allows the importance of emotional and cognitive influences in investment decision-making, enabling more accurate and adaptable financial strategies. They found that the status of the firm getting affluent speedily, the firm status in the industry, and the firm's goods and services influence the firm-image factor [2]. Similarly, coworker's or friend recommendations, broker recommendations, and family member opinions are the most influencing supporter suggestion factors. Furthermore, return exploitation, obtaining borrowed funds, stock marketability, and expected dividends influence personal financial needs. Information on the stock market, information on dividends and past stock trends, and the price level of other stocks influence market information factors. Firm image, supporter recommendation factor, personal financial requirements factor, and market information factor influence the ID of individual depositors [14].

Muhammad et al. (2020) [10] identified that ID was influenced by behavioral finance biases (Prospect theory, Heuristic behavior, and Personality Characteristics). The actual results showed that changes, heuristic behaviors, and personality characteristics influenced IDM. The research findings benefit financial institutions and depositors who plan decisions by analysing psychological factors. They tells that the four behavioral factors, prospect, herding, heuristic, and market, have influenced the return on investment and investment decisions.

AI has changed the field of finance by providing advanced tools for analyzing data, generating predictions, and making decisions [20]. Machine learning algorithms have analyzed large financial data, allowing more accurate forecasts and risk evaluations.

According to recent research, AI can decrease the impact of behavioral biases by providing neutral analysis and suggestions. However, [16] claim that algorithms have the potential to strengthen current prejudices by matching or improving human actions if they are not properly managed.

Due to their great knowledge and technology experience, IT/ITES industry personnel are more prepared to use artificial intelligence (AI) when making investment choices. However, their cognitive biases and risk preferences importantly impact molding outcomes. The relationship between AI tools and behavioral characteristics within this group has yet to be well investigated, making it an essential field of research [17].

Waweru et al. (2008) found that market factors have a positive influence on depositors' DM: market information, price changes, customer preference, past trends of the stock, fundamentals of the underlying stock, and overreaction to price changes have a greater influence on depositors' DM behavior [19]. Heuristic behaviors have the maximum positive impact on investment performance. At the same time, future behavior had a damaging crash on investment performance. Similarly, four factors (herding, opportunity, heuristics, and market) directly affect investment decisions. Confidence is significantly influenced by heuristic variables (availability, anchoring, representation, and the fallacy of gambling) except overconfidence. The Anchoring Heuristic Representative Disposition Effect positively impacts depositors' DM. High heuristic and trust damaged depositors' DM [1].

On the same basis, market factors are high; second is grouping influencing factors (herding), third is prospective factors, and fourth is heuristic variables influencing the investment decision. BF such as anchoring, overconfidence, availability bias, representation, and gamblers' fallibility were positively related to investment performance. On the other hand, mental accounting, loss aversion, and regret aversion were negatively related to investment performance.

METHODOLOGY

Data were collected on Behavioral Finance (BF) and the Investment Decision Process (IDP) from 142 IT/ITES employees out of 170 selected respondents. This research employed a descriptive design, with questionnaires distributed to IT/ITES employees via Google Docs. We gathered the responses using a categorical and Likert scale format, measuring reactions to queries on a five-point scale (choices ranging from 1 to 5). This approach facilitates the application of more robust statistical methods to test the study's hypotheses.

The IDP component consisted of five statements, which IT/ITES employees responded to on a five-point scale. Samina Gill (2018) [13] constructed and standardized the tool for measuring 'Behavioral Factors,' while [8] classified another set of statements related to Behavioral Factors on a five-point scale into four distinct factors.

Incorporating AI into this research adds a new dimension to data analysis, enabling the identification of patterns and insights that may not be immediately apparent through traditional methods. AI can analyze responses more effectively, providing deeper insights into the behavioral tendencies of IT/ITES employees.

S.No.	Variable	Items	Total Items
	Behavioral Factors	**1 to 71**	**22**
1	Heuristic	1 to 7	7
2	Prospect	8 to 13	6
3	Market	14 to 18	5
4	Herding	19 to 22	4

They selected 170 IT/ITES employees for the research in Chennai city. The questionnaire was constructed by the researcher and distributed to the IT/ITES employees through a Google document. The researcher clearly explained the nature of the research to the IT/ITES employees. IT/ITES employees voluntarily agreed to answer the questionnaire. Also, the collected data were analyzed and tabulated using SPSS software to determine the consistency and strength of the research tool.

The reliability of the questionnaire was evaluated through a pilot study. Reliability (Cronbach alpha) of not less than 0.6 for all constructs was considered sufficient for the research. This research used Cronbach's alpha to check the consistency of the research tool. Instrument reliability of 0.6 and above is acceptable [12]. Reliability and validity are the criteria of a good instrument. Reliability and validity are the primary purposes of reliability testing, which is to increase the eminence of the research instrument. The reliability of the research instrument refers to the consistency of the research. Data were collected from 124 IT/ITES employees in Chennai for the pilot study. Correlation analysis was done to identify the validity. At the same time, the table value was found to be 0.273 at a five percent level. The table values indicate that the set questionnaire was correct at the five percent level. Therefore, the questionnaire was designed to make this study more valid. The questionnaire was taken to the next stage of the study as the value detected by the valid analyzer was more significant than 0.273. The primary data collected will be analyzed by the researcher using statistical tools. According to the hypotheses constructed in this study, the researcher will analyze using some statistical tools (CFA and SEM).

RESULTS AND DISCUSSION

In fig 1 and 2 shows the model fit results indicate the impact of BF on IDP. The table 1 values exposed in CFA fit procedures for the goodness of fit are $\chi 2$ = 385.001, AGFI = 0.830, GFI = 0.903, CFI = 0.960, and NFI = 0.923, which are within the satisfactory range. Correspondingly, the badness of fit values is RMR = 0.084 and RMSEA = 0.079, which are also within the satisfactory range. Indra et al. (2020) found a related result [5].

TABLE 1. Model Fit Indication of CFA

	S.No.	Model Fit Indicators	Suggested standards [11]	Calculated Values
Chi-Square Test	1	Chi-Square	---	385.001
	2	p		0.0001
Goodness Fit	3	GFI	> 0.90	0.903
	4	AGFI		0.830
	5	CFI		0.960
	6	NFI		0.923
Badness Fit	7	RMR	< 0.080	0.084
	8	RMSEA		0.079

****** Source***: *Primary data*

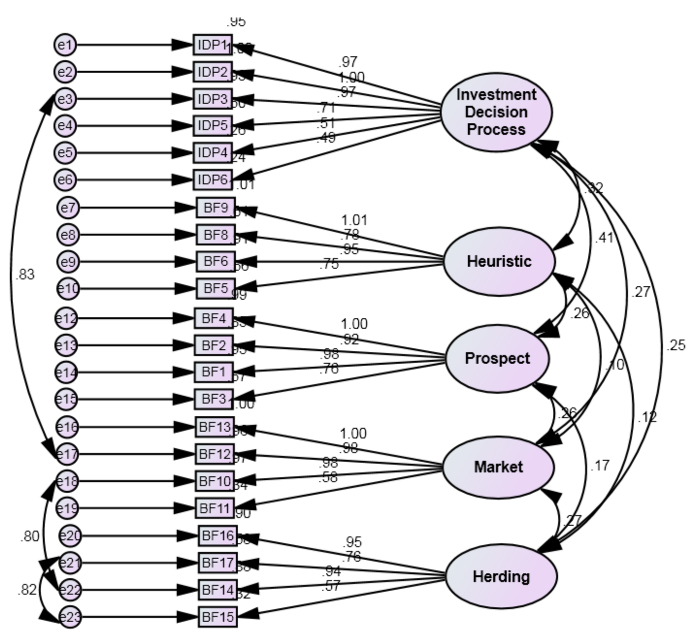

FIGURE 1: CFA of the impact of BF on IDP

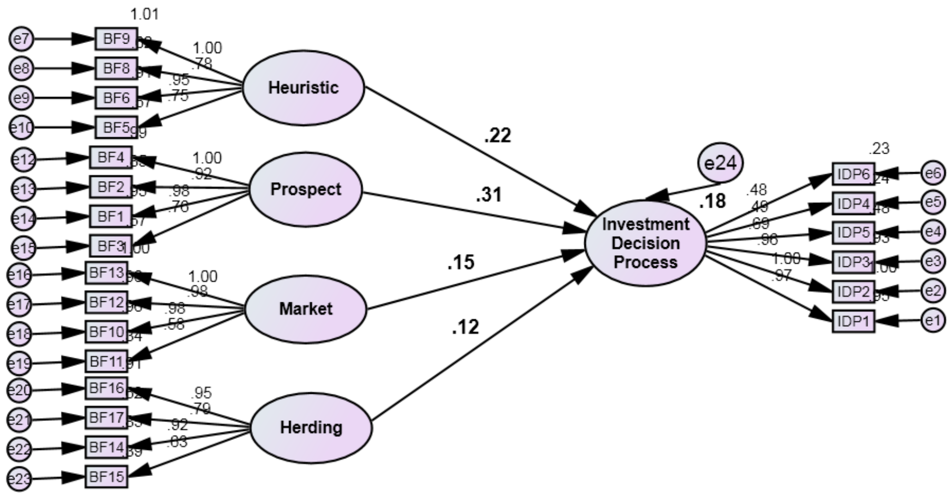

FIGURE 2: Impact of BF on IDP

TABLE 2. Model fit indication of SEM

	S.No.	Model Fit Indicators	Suggested standards [11]	Calculated Values
Chi-Square Test	1	Chi-Square	---	432.054
	2	p		0.0001
Goodness Fit	3	GFI	> 0.90	0.931
	4	AGFI		0.831
	5	CFI		0.951
	6	NFI		0.914
Badness Fit	7	RMR	< 0.080	0.079
	8	RMSEA		0.087

In table 2 the model fit results indicate the impact of BF on IDP. The table values exposed in CFA fit procedures for the goodness of fit are $\chi 2$ = 432.054, AGFI = 0.831, GFI = 0.931, CFI = 0.951, and NFI = 0.914, which are within the satisfactory range. Similarly, the badness of fit values is RMR = 0.079 and RMSEA = 0.087, which are also within the satisfactory range. Indra et al. (2020) found a related result [5].

TABLE 3. Regression Weights of SEM

DV		IV	Estimate	SE.	CR.	Beta	P
IDP	<---	Heuristic	0.241	0.079	3.036	0.221	0.002
IDP	<---	Prospect	0.323	0.077	4.176	0.326	0.001
IDP	<---	Market	0.129	0.061	2.119	0.154	0.014
IDP	<---	Herding	0.160	0.097	1.655	0.124	0.038

In table 3 Hypothesis H1 of the research clarifies that heuristics significantly influence the IDP of IT/ITES employees towards behavioral finance. The research outcomes indicate that the beta coefficient and the t-value were significant (p=0.002). The value of β is 0.221, and the heuristics of the behavioral factor explain 22.1 percent of the IDP of IT/ITES employees towards behavioral finance. Consequently, statistical outcomes ascertain a positive influence of heuristics of behavioral factors on the IDP of IT/ITES employees towards behavioral finance. The prospect theory offered [7][18] has similar results, as it explicates that the investment option's outcome is based on the depositors heuristics biases.

Hypothesis H2 of the research clarifies that prospects significantly influence the IDP of IT/ITES employees towards behavioral finance. The research outcomes indicate that the beta coefficient and the t-value were significant (p=0.001). The value of β is 0.326, and the prospect of the behavioral factor explains 32.6 percent of the IDP of IT/ITES employees towards behavioral finance. Consequently, statistical outcomes ascertain a positive influence of the prospect of behavioral factors on the IDP of IT/ITES employees towards behavioral finance. The prospect theory offered [7][18] has similar results, as it explicates that the outcome of investment options is based on the prospect biases of the depositors.

Hypothesis H3 of the research clarifies that the market has significant influences on the IDP of IT/ITES employees toward behavioral finance. The research outcomes indicate that the beta coefficient and the t-value were significant ($p=0.014$). The value of β is 0.154, and the market of behavioral factor explains 15.4 percent of the IDP of IT/ITES employees towards behavioral finance. Consequently, statistical outcomes ascertain a positive influence of the market of behavioral factors on the IDP of IT/ITES employees towards behavioral finance. The market theory offered [7][18] has similar results, as it explicates that the outcome of investment options is based on the market biases of the depositors.

Hypothesis H4 of the research clarifies that herding significantly influences the IDP of IT/ITES employees towards behavioral finance. The research outcomes indicate that the beta coefficient and the t-value were significant ($p=0.038$). The value of β is 0.124, the herding of behavioral factors explains 12.4 percent of the IDP of IT/ITES employees towards behavioral finance. Consequently, statistical outcomes ascertain a positive influence of the herding of behavioral factors on the IDP of IT/ITES employees towards behavioral finance. The herding theory offered [7][18] has similar results, as it explicates that the outcome of the investment option is based on the herding biases of the depositors.

CONCLUSIONS

The research offers valuable recommendations for behavioral finance officials and policymakers, particularly on how individual behavioral biases among depositors can be strategically harnessed to maximize investment returns and increase wealth. Integrating AI into these strategies can significantly improve IT/ITES employees' savings. This research provides multi-dimensional operational insights that can guide depositors in making informed decisions across various behavioral finance schemes. Additionally, AI-driven insights enable behavioral fund program managers to understand better and anticipate depositors' heuristic behaviors. For IT/ITES employees, AI can play a crucial role in managing business activities and formulating more effective investment strategies. By gaining AI-powered insights into market variables such as how depositors react to changes in investment volume and behavioral financial plans investors can make more informed decisions. Investment advisors at behavioral finance firms can leverage AI to analyze individual decision-making behaviors, allowing for a more personalized approach to dealing with depositors. Augmented by AI, behavioral funds empower fund managers to understand investor behavior more deeply, offering improved investment opportunities that align with each investor's unique needs and tendencies.

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