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Integrating Behavioural Finance Into Strategic Investment Evaluation: A Fuzzy Logic

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Abstract: *In the recent era of growing awareness, the investment decision making process is not only evaluated by the quantitative parameters but also the psychological constructs of the investors. This study attempts to apply the Fuzzy logic of Analytic Hierarchy Process to evaluate the investment strategies adopted by the individual. The Fuzzy Logic AHP model designed can be used by the analyst or the advisors to rank the strategies with respect to the multiple criteria that influence the investment decision making process. The study uses the Saaty Scale to convert the linguistic statements provided by the experts for the pair wise comparisons of the criteria and the investment strategies. The study suggests that Trading frequency has the maximum weights derived and followed by Asset Allocation. The AHP- FUZZY logic can be further extended by using other criteria and factors impacting the investment decision making process under different decision-making situations.*

Keywords: *behavioural biases, sentiment index, investment strategy, AHP, fuzzy logic.*

INTRODUCTION

Traditional investment evaluation has stringently relied on the rational decision-making frameworks rooted in classical financial theories such as Net Present Value (NPV), Internal Rate of Return (IRR), and Discounted Cash Flow (DCF) analysis. As per the assumptions of the traditional theories, it has been assumed that the investors act rationally, look forward to achieve maximum utility and have access to complete and accurate information. On the contrary, the investment decisions making process often deviate from the assumptions of the traditional theories and ideal circumstances. It is evident from the previous studies that the psychological factors and cognitive biases significantly influence investors' behaviour leading to the suboptimal investment choices (Almansour & Arabyat, 2017). The inclusion of the psychological constructs in the decision-making process gives rise to behavioural finance, a field that integrates insights from psychology into financial theory to explain market anomalies and irrational investor actions.

Despite growing awareness, the integration of behavioural insights into strategic investment evaluation remains limited, particularly in formal decision-making tools. Human judgments are frequently imprecise, subjective, and consistent- especially under conditions of uncertainty and risk. Traditional quantitative models may fail to capture this vagueness and the nuanced impact of behavioural biases. This study will focus on the impact of the behavioural biases such as overconfidence, herding, anchoring, loss aversion and confirmation bias. There are evidences found from the literature that the investors' sentiment index also impacts on the decision making of the individual (Ahmad, 2022; Lather et al., 2020; Menon et al., 2023). This study intends to derive the weightages of the considered criterions and their impact on the investment strategies by using multi criteria decision making process.
This study proposes a novel framework that integrates Behavioural Finance principles with Fuzzy Logic. Fuzzy Logic, with its ability to model ambiguity and human reasoning, offers a powerful method for incorporating qualitative judgments and behavioural nuances into strategic investment evaluation. Unlike binary logic, fuzzy

systems accommodate degrees of truth, making them particularly suited to capturing the imprecise nature of human decision-making.

This paper aims to develop a behavioural-financial fuzzy evaluation model that reflects both the rational and behavioural dimensions of investment decisions. By doing so, it bridges the gap between normative financial theories and actual investor behaviour, offering a more comprehensive and realistic tool for strategic investment assessment.

LITERATURE REVIEW

The foundation of evaluating investments has long been established by traditional financial decision-making instruments like Net Present Value (NPV), Internal Rate of Return (IRR), and Discounted Cash Flow (DCF) models. Modern Portfolio Theory (MPT) and the Efficient Market Hypothesis (EMH) serve as the foundation for these models, which make the assumptions that markets are efficient, investors are rational, and decisions are made using factual information (Markowitz, 1952; Fama, 1970). However, because of human error, complexity, and ambiguity, these presumptions frequently fall short in practice.
Conventional capital budgeting instruments, such as NPV and IRR, rely on the availability of precise projections and logical decision-making. However, real-world strategic expenditures frequently depend significantly on subjective assessments and include a considerable degree of uncertainty. Incomplete evaluations result from the frequent exclusion of managerial biases and qualitative elements from formal analysis, as Ryan and Ryan (2002) point out. Furthermore, Chapman (2006) points out that, particularly in intricate, high-stakes investment contexts, decision-makers usually rely on heuristics rather than rigorous probabilistic logic. Behavioural Finance emerged as a response to the anomalies unexplained by classical models.

Pioneers such as Kahneman and Tversky (1979) introduced Prospect Theory, which demonstrated that individuals value gains and losses differently, often leading to irrational decisions. Their studies have identified a range of behavioural biases, like, Overconfidence Bias: Investors overestimate their knowledge and predictive ability (Barber & Odean, 2001); Loss Aversion: Losses loom larger than gains, leading to risk-averse behavior in gain scenarios and risk-seeking in loss scenarios (Kahneman & Tversky, 1979); Herding Behavior: Investors mimic the actions of others rather than relying on their own analysis (Bikhchandani & Sharma, 2001) and; Mental Accounting: People treat money differently depending on its source or intended use (Thaler, 1999). These biases significantly impact investment choices, yet they are often overlooked in traditional evaluation frameworks.

Behavioural finance has advanced beyond early models by categorizing and quantifying biases that affect investor and managerial decisions. Recent meta-analyses (Baker & Ricciardi, 2015) show consistent evidence that biases such as anchoring, representativeness, and framing have a substantial effect on investment evaluation processes. In addition, anchoring can distort forecasts and valuation metrics, framing effects influence risk perception based on how choices are presented, and availability heuristic leads to overweighing recent or easily recalled information when making investment decisions (Tversky & Kahneman, 1974; Levin et al., 1998 and Sunstein, 2000). Therefore, understanding and integrating these behavioural tendencies is essential to improving strategic financial decision-making.

Unlike individual investors, strategic investment decisions are often made by corporate managers, whose behaviour is also influenced by biases. Studies such as Brealey, Myers, and Allen (2011) show that managers tend to overestimate project success rates due to optimism bias. Furthermore, Buehler, Griffin, and Ross (1994) identified planning fallacy, where managers underestimate completion times and costs, as a recurrent issue in project-based investment decisions.
These behavioural distortions are rarely accounted for in quantitative models, suggesting a need for tools that can capture such psychological influences. Recent literature emphasizes the importance of incorporating behavioural factors into investment models.

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Shefrin (2007) and Statman (2010) argue that behavioural finance should complement, not replace, traditional models. However, integrating qualitative biases into quantitative frameworks remains a methodological challenge. Scholars have suggested multi-criteria decision-making (MCDM) and heuristic-based models, but these still often rely on precise inputs, which may not reflect the ambiguity in human judgment.

Fuzzy Logic, introduced by Zadeh (1965), provides a mathematical approach to deal with imprecision and vagueness in human reasoning. It enables the modeling of subjective judgments using linguistic variables and fuzzy numbers. In investment analysis, fuzzy logic has been applied to areas such as project risk assessment (Kahraman et al., 2003), capital budgeting (Buckley, 1987), and portfolio selection (Huang, 2006). Its ability to handle uncertain, incomplete or imprecise data makes fuzzy logic is an ideal tool to integrate behavioural elements into investment evaluation. By allowing for gradation in preferences and beliefs, fuzzy systems offer a flexible and realistic approach to modelling investor behaviour.

FUZZY LOGIC AND MULTI-CRITERIA DECISION MAKING (MCDM) IN INVESTMENT ANALYSIS

Fuzzy logic is increasingly used in conjunction with multi-criteria decision-making (MCDM) methods to address the subjective and imprecise nature of strategic decisions. Fuzzy AHP (Analytic Hierarchy Process) allows the incorporation of expert judgment under uncertainty (Van Laarhoven & Pedrycz, 1983), Fuzzy TOPSIS ranks investment alternatives based on closeness to an ideal solution, while tolerating imprecise evaluations (Chen, 2000), and Fuzzy DEMATEL helps to understand causal relationships among behavioural and financial variables (Li & Tzeng, 2009). These methods have been used in areas like risk assessment, supply chain finance, and portfolio selection but are less frequently applied to strategic investment decisions influenced by behavioural factors.

Recent research has attempted to operationalize behavioural traits within fuzzy decision models. Sahi, Arora & Dhameja (2013) developed a behavioural finance-based investment decision model, emphasizing psychological profiling. On the other hand, Deng & Hendry (2017) proposed a fuzzy rule-based model to assess the impact of overconfidence and risk perception on investment project selection. Also, Zhou et al. (2020) integrated behavioural factors into fuzzy Bayesian networks for dynamic decision-making under uncertainty. These studies suggest that fuzzy logic offers a promising platform to blend qualitative human traits with structured quantitative analysis in financial decision-making.

A growing body of research has begun to merge behavioural finance with fuzzy methodologies. For instance, Yalçın et al. (2012) employed fuzzy AHP to prioritize investor preferences influenced by behavioural traits. Similarly, Pamučar and Ćirović (2015) used fuzzy MCDM models to incorporate subjective judgments into strategic decision-making. These studies demonstrate the potential of fuzzy logic to bridge the gap between behavioural insights and formal investment evaluation tools.

However, there remains a gap in developing a comprehensive, behaviourally informed fuzzy framework specifically tailored for strategic investment evaluation—one that not only recognizes behavioural biases but also integrates them systematically into the decision-making process.

GAP IN EXISTING LITERATURE

While the fusion of fuzzy logic and behavioural finance is gaining attention, there remains a lack of a comprehensive, integrated framework that simultaneously addresses Strategic-level investment evaluations, Managerial behavioural biases, and the inherent vagueness in qualitative judgments. Moreover, there is limited empirical validation of such integrated models in corporate or institutional investment contexts. This gap underscores the need for a hybrid framework that not only reflects behavioural dynamics but also enhances the robustness of strategic investment evaluations.

The existing literature highlights a clear disconnect between traditional rational investment models and actual investor behaviour influenced by psychological biases. While behavioural finance provides insights into these biases, and fuzzy logic offers tools to manage uncertainty, an integrated model that combines both remains

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underexplored. This study aims to fill this gap by proposing a fuzzy logic-based strategic investment evaluation model enriched with behavioural finance principles.

RESEARCH METHODOLOGY

RESEARCH OBJECTIVES

The objectives of the paper are:

1. To derive the weightage of the multiple criterions impacting the investment strategies.
2. To rank the investment strategies on the basis on the weightages of the criterions.

On the basis of the expert judgements, which includes the interview extracts of the financial advisors and Industrialists extracted from textual databases and online forums and content analysis of a textual database comprising of academic journals, newspaper articles and data collected from experts as financial advisors and consultancies, the criteria for investment decisions are established. Table 1: It shows that behavioural biases such as overconfidence, herding, anchoring, loss aversion and confirmation bias are the maximum occurring psychological and cognitive biases among the investors. The analysis also reveals that the sentiment index or emotional quotient of the investors also influences the investors in the decision-making process. This study will attempt to develop a Fuzzy logic model by applying Analytical Hierarchical Process (AHP) of multiple criteria decision-making methods. The outcome of the study will reveal the weightages of the criterion considered for the framework and it also helps to evaluate the strategies adopted for investment decisions.

Table 1: Textual Database for Content Analysis

Types Textual Data	Numbers of Documents
Research Papers	120
Academic Thesis	50
Articles Published	100
Expert Judgements	45

Source: Author Generated

As per the content analysis of the textual corpus it has been established that the sentiment of the investors and the behavioural prejudices are the maximum occurring factors that impacts the investment decision making process. Table 2 highlights the behavioural biases identified in the textual corpus which are taken into consideration for developing the AHP Fuzzy Logic Model. As per the expert judgements, it can be concluded that the investment decisions mainly revolve around allocation of funds across the different investment options, the time required to remain invested, frequency of trading or transactions and diversification strategy.

Table 2: Behavioural Bias Identified

Bias Identified
Over confidence
Anchoring
conservatism, loss aversion, framing bias
mental accounting, loss aversion
Anchoring
Over confidence and anchoring
Over confidence and anchoring
Ambiguity aversion
Anchoring
Anchoring, conservatism
Anchoring
Overconfidence, disposition, herd behaviour
Disposition, self attribution, overconfidence
Self attribution bias
anchoring
conservatism, loss aversion, framing bias
Self attribution bias, anchoring
illusion of control, overconfidence, anchoring
Loss aversion, conservatism bias
Availability, Representativeness, Overconfidence, Anchoring and Gambler's Fallacy.
Overconfidence, disposition, herd behaviour, Framing
Ambiguity aversion, conservatism bias
overconfidence, disposition, herding, optimism, home bias

Source: Author Generated

CONCEPTUAL FRAMEWORK

A. Independent Variables (Behavioural Factors)

These are the behavioural biases and sentiments influencing investment decisions:

- Overconfidence Bias: Overestimation of knowledge and control over outcomes.
- Loss Aversion: Preference for avoiding losses more than acquiring equivalent gains.
- Herding Behaviour: Tendency to follow the actions of a group rather than individual analysis.
- Anchoring Bias: Relying heavily on initial information when making decisions.
- Confirmation Bias
- Investor Sentiment: General mood or outlook of investors, influenced by market news, social media, etc.

B. Mediating Variable

FUZZY LOGIC-BASED DECISION MODEL

A fuzzy multi-criteria decision-making system serves as an intermediary between behavioural factors and decision outcomes. This includes methods such as Fuzzy AHP and Fuzzy TOPSIS. These models help to translate qualitative judgments and uncertain preferences into quantifiable decision parameters.

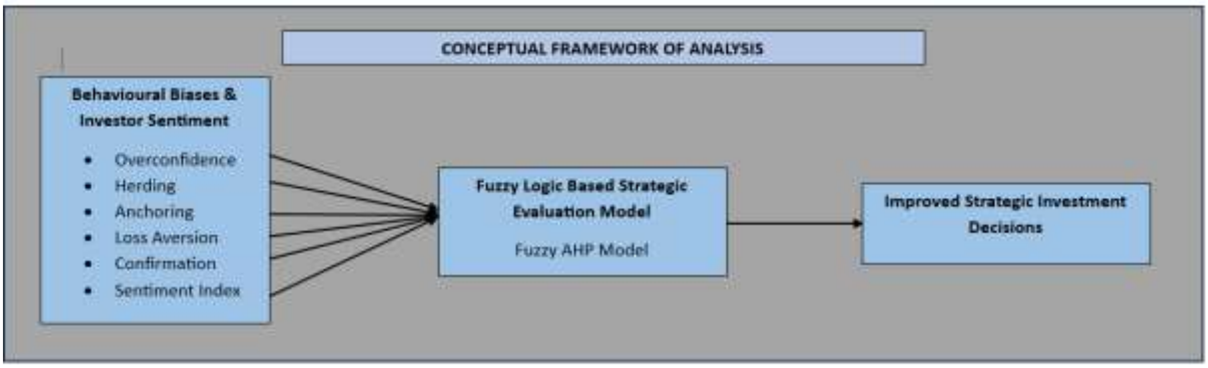
C. Dependent Variable Strategic Investment Decision Quality

Strategic Investment Decision Quality refers to the effectiveness and soundness of investment decisions made by investors. It is evaluated through the following key dimensions:

- Asset Allocation
- Investment Horizon
- Trading frequency
- Diversification Strategy

CONCEPTUAL FLOW EXPLANATION

- **Step 1:** Investors and managers are influenced by behavioural biases and sentiments, which introduce subjectivity and uncertainty in evaluating investment alternatives.
- **Step 2**: These subjective factors are captured using linguistic variables and processed through a fuzzy logic model.
- **Step 3:** Fuzzy systems translate imprecise, uncertain data into structured, rationalized outputs for evaluating and comparing strategic investment options.
- **Step 4:** The integration of behavioural finance into fuzzy models improves the realism, reliability, and effectiveness of investment decisions.



Analysis and Interpretation

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On the basis of the data collected from the experts, the observations are converted from linguistic statements to ratings as per Saaty Scale. The initial matrix of the pair wise comparison of the constructs is then converted into the Triangular Fuzzy scale (Rivza and Rivza (2013).

Table 3: Triangular Fuzzy Scale

Linguistic Term	TFN (Low)	TFN (Medium)	TFN (High)
Equally Important	1	1	1
Slightly More Important	2	3	4
Moderately More Important	4	5	6
Strongly More Important	6	7	8
Very Strongly More Important	8	9	10
Extremely More Important	9	9	9

Source: Rivza and Rivza (2013)

The initial matrix of the fuzzy ratings is then adjusted on the basis of geometric mean to get the fuzzy weights. The fuzzy weights are then averaged and normalized to get the weights of the constructs which are mentioned as per Table 4. As per the weights derived, sentiment index derives the maximum weights of 0.36 followed by overconfidence with weights of 0.24 and herding behaviour bias with weights of 0.14. The constructs of loss aversion and confirmation are not of significance weights to influence the investment decision strategies. The weights derived, as per the Table 4, will be further incorporated into the further analysis.

Table 4: Derived weights of the Criteria

Weights of the criteria					
	Fuzzy Weight			Average	Normalized
Sentiment Index	0.203424383	0.374867556	0.65178385	0.410025263	0.360997734
Overconfidence	0.125658226	0.243437829	0.465864965	0.27832034	0.245041028
Herding	0.070523295	0.140548896	0.269524715	0.160198969	0.141043662
Anchoring	0.052882524	0.106331266	0.224428696	0.127880829	0.112589866
Loss Aversion	0.03923018	0.064539062	0.123507871	0.075759038	0.06670038
Confirmation	0.041972887	0.070274448	0.138632898	0.083626744	0.07362733
Total				1.135811183	1

Source: Author Generated

The next stage is followed by deriving the weights of the investment strategies with respect to the sentiment of the investors. As per the logics behind the expert judgements, Trading frequency is highly influenced by sentiment which results into panic selling, and Fear of missing out buying of the investments. The experts also revealed that asset allocation is moderately influenced as sentiment may change the preferences, for instances risk-on vs. risk - off. As per the experts, the investment horizon is not much influenced by the sentiment due to the focus of the longer term. Similarly, it has been stated that diversification strategies are relatively less impacted by the sentiment. The fuzzy weights derived from the Triangular Fuzzy Matrix are shown in the **Table 5.** As per the weights derived, Trading Frequency (TF) has the maximum weights 0.46 which can be interpreted as trading frequency gets most impacted by the sentiment of the investors which is followed by the asset allocation with weights of 0.27.

Table 5: Derived Weights of the Investment Strategies with respect to Sentiment

WRT-Sentiment	Fuzzy Weights			Average	Normalized
Asset Allocation	0.139542825	0.271717157	0.536994664	0.316084882	0.278608431
Investment Horizon	0.053014809	0.088217843	0.171554519	0.10426239	0.091900571
Trading Frequency	0.259718461	0.483189025	0.840442069	0.527783185	0.465206828
Diversification Strategy	0.08297266	0.156875974	0.319298938	0.186382524	0.16428417
Total				1.134512981	1

Sources: Author Generated

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According to the expert judgements, overconfidence often results to excessive trading and under estimation of risk. Therefore, Trading Frequency (TF) is the most influenced by overconfidence bias. The experts also suggested that asset allocation gets moderately influenced by over confidence for example, over confidence can cause over weighting in risky assets.

The experts also suggested that investment horizon (IH) is less influenced, over-confident investors may shorten horizons but it is a relatively stable strategic choice. Similarly, diversification strategy is typically undermined by confidence, as investors may belief they can "beat the market" without diversification. The fuzzy weights and the normalized weights of the pair wise matrix have been provided by the Table 6. As per the Table 6, Trading frequency gets the maximum weights of 0.46 followed by the asset allocation of 0.27. It can be interpreted as that over confidence bias impacts the trading frequency and asset allocation supporting the experts' judgements.

Table 6: Derived Weights of the Investment Strategies with respect to Overconfidence

WRT -Overconfidence	Fuzzy Weights			Average	Normalized weights
Asset Allocation	0.139542825	0.271642835	0.536994664	0.316060108	0.278608985
Investment Horizon	0.053014809	0.088193713	0.171554519	0.104254347	0.091900867
Trading Frequency	0.259718461	0.483056861	0.840442069	0.52773913	0.465205383
Diversification Strategy	0.08297266	0.156833064	0.319298938	0.186368221	0.164284766
Total				1.134421806	1

Source: Author Generated

Table 7: Derived Weights of the Investment Strategies with respect to Herding

WRT -Herding	Fuzzy Weights			Average	Normalized weights
Asset Allocation	0.153258885	0.287908055	0.555341672	0.332169537	0.29444553
Investment Horizon	0.049758243	0.080951299	0.151614988	0.094108177	0.083420449
Trading Frequency	0.257749694	0.476451975	0.821997644	0.518733104	0.459821347
Diversification Strategy	0.082343695	0.154688669	0.312291572	0.183107979	0.162312674
Total				1.128118797	1

The experts suggested that herding inspires the investors to follow the behaviour of the other investors regardless of the analysis or their own judgements. As per the expert's opinion the herding bias of the investors significantly influences the trading frequency which includes the buying, selling and holding of the investment instruments due to market movements. According to the analysts investigated, it was found that the herding behaviour also influences the asset allocation strategies. The investors generally follow the reference groups to invest which in turn impacts their portfolio returns. The experts also highlighted the fact that the diversification strategies are also affected moderately as herding behaviour may cause under diversification of the portfolio. As per the suggestions, it is being revealed that the herding behaviour comes to the play for the short-term investment options. Therefore, it can be concluded that the investment horizon gets least affected by the herding bias of the investors. Table 7 reveals the weightages of the investment strategies with respects to the herding behaviour. After going through the conversion process of the initial pair wise matrix of the experts to the fuzzy triangle, fuzzy weights have been derived which have been normalized and defuzzied to derive the actual weightage of the investment strategies. The Table 7 highlights the fact that asset allocation and trading frequency are significantly related with the herding bias of the investors with weights of 0.29 and 0.45 respectively, establishing the experts' views.

Table 8: Derived Weights of the Investment Strategies with respect to Anchoring

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WRT -Anchoring	Fuzzy Weights			Average	Normalized weights
Asset Allocation	0.244927454	0.466848564	0.8270222	0.512932739	0.449225141
Investment Horizon	0.141408932	0.277589817	0.553063078	0.32	0.283776395
Trading Frequency	0.084082254	0.160266556	0.328853274	0.191067361	0.167336291
Diversification Strategy	0.056229192	0.095295064	0.189863526	0.113795927	0.099662173
Total				1.141816637	1

Source: Author Generated

The experts suggested that when the investors depend overly on the initial reference points for instances, initial assets weights, buying quotes or prices, expense ratios or any other parameters or forecasts then anchoring bias occurs. As per the experts' comments, the anchoring bias has a significant and positive relation with the asset allocation as the investors influenced with anchoring bias may remain invested with the existing portfolios regardless of the changes in the risks or returns, due to the initial references. Simultaneously the anchoring behaviour of the investors might also impact the investment horizon strategies as they possess a tendency to hold the investments longer than the desired or warranted time period due to past valuations. The experts rated the trading frequency as moderately impacted with respect to anchoring as it may cause delay or hasten the trades. The statements provided by the experts are converted into the initial pair wise matrix as per the Saaty Scale, which further gets converted into the fuzzy triangle to derive the fuzzy weights of the investment strategies as shown in the Table 8. On defuzzification of the weights as per the central distance methods the normalized weights of the decision-making units are derived. The normalized weights of the strategies establish the comments of the experts. As per the normalized weights the asset allocation and investment horizon strategies are significantly affected by the anchoring bias of the investors with respective weights of 0.44 and 0.23. The trading frequency also gets moderately affected as the weights derived as 0.16 with respect to the anchoring bias. As per the experts the diversification strategy is the least affected with respect to anchoring.

Table 9: Derived Weights of the Investment Strategies with respect to Loss Aversion

WRT -Loss Aversion	Fuzzy Weights			Average	Normalized weights
Asset Allocation	0.152540427	0.284242599	0.541107868	0.325963631	0.291274115
Investment Horizon	0.048237518	0.076359637	0.133488209	0.086028455	0.076873184
Trading Frequency	0.097464654	0.16901166	0.326978	0.197818105	0.176766019
Diversification Strategy	0.256541396	0.470386101	0.800929257	0.509285585	0.455086683
Total				1.119095776	1

Source: Author Generated

It has been found in the literature that loss aversion refers to the behaviour to fear losses more than valuing gains. The experts suggested that the loss aversion behaviour affects asset allocation which may results in avoidance of the riskier assets. It also significantly impacts the diversification strategy that used to reduce potential gains. The experts also suggested that trading frequency is moderately affected which might cause holding the investments for too long or sell them too early. The investment horizon is relatively less affected as longer horizons often buffer emotional responses to short term losses. The normalized weights of the fuzzy matrix establish the facts opined by the experts with the weights of 0.45 of diversification strategy and asset allocation with the weight of 0.29.

Table 10: Derived Weights of the Investment Strategies with respect to Confirmation

WRT -Confirmation	Fuzzy Weights			Average	Normalized weights
Asset Allocation	0.244927454	0.466848564	0.8270222	0.512932739	0.379376527
Investment Horizon	0.084082254	0.160266556	0.328853274	0.191067361	0.141317694
Trading Frequency	0.141408932	0.277589817	0.553063078	0.324020609	0.23965289
Diversification Strategy	0.056229192	0.095295064	0.189863526	0.324020609	0.23965289
Total				1.352041318	1

Source: Author Generated

Literature suggests that confirmation bias refers to the behaviour according to which the investors favours information that supports or justifies the beliefs while ignoring contradictory evidence. According to the experts the confirmation bias significantly impacts asset allocation resulting in which the investors stick with preconceived beliefs about certain asset class. The experts also suggested that the confirmation bias influence the trading frequency as the investors may trade more based on affirming signals. It moderately affects investment horizon according to which the investors may remain committed to a biased long or short horizon. The confirmation bias has least effect on diversification strategy. Experts suggested that confirmation bias is less relevant when spreading risk is the goal. As per Table 10, Asset allocation is mostly affected by the confirmation bias followed by trading frequency and diversification strategy with weights 0.37 and 0.23 respectively.

Table 11: Weights of the criteria and the investment strategies

	weights	AA	IH	TF	DS
Sentiment Index	0.36	0.27	0.09	0.46	0.16
Overconfidence	0.24	0.27	0.09	0.46	0.16
Herding	0.14	0.29	0.08	0.45	0.16
Anchoring	0.11	0.44	0.28	0.16	0.09
Loss Aversion	0.06	0.29	0.07	0.17	0.45
Confirmation	0.07	0.37	0.14	0.23	0.23

Source: Author Generated

Table 12: Ranking of the investment strategies with respect to the criteria

	AA	IH	TF	DS
Sentiment Index	0.0972	0.0324	0.1656	0.0576
Overconfidence	0.0648	0.0216	0.1104	0.0384
Herding	0.0406	0.0112	0.063	0.0224
Anchoring	0.0484	0.0308	0.0176	0.0099
Loss Aversion	0.0174	0.0042	0.0102	0.027
Confirmation	0.0259	0.0098	0.0161	0.0161
Sum	0.2943	0.11	0.3829	0.1714

Source: Author Generated

By using the weights of the criteria influencing the investment decision making process and the weights of the investment strategies are normalized by adopting the centroid method. The weights derived suggests that trading frequency is mostly influenced by the criteria considered for the study such as sentiment index, overconfidence, herding, anchoring, loss aversion and confirmation bias with weight 0.38 which is followed by the asset allocation with the weight 0.29.

CONCLUSION AND FUTURE SCOPE

As per the weights derived from the AHP- fuzzy model it can be interpreted that the investment strategies such as trading frequency gets the maximum influenced by the sentiment index and behavioural biases of the investors with the max weights of 0.38 which is followed by asset allocation with weights 0.29 whereas the investment strategies such as investment horizon and diversification strategies gets less impacted comparatively as they are mostly affected by sentiments and overconfidence bias. The study can be further extended with other factors that affect the investment decision making process and strategies adopted by the investors.

REFERENCES

1. Ahmad, M. (2022). The role of cognitive heuristic-driven biases in investment management activities and market efficiency: A research synthesis. International Journal of Emerging Markets. https://doi.org/10.1108/IJOEM-07-2020-0749

2. Almansour, B. Y., & Arabyat, Y. A. (2017). Investment decision making among Gulf investors: Behavioural finance perspective. International Journal of Management Studies, 24(1), 41–71.
3. Baker, H. K., & Ricciardi, V. (2015). Understanding behavioral aspects of financial planning and investing .Journal of Financial Planning, 28(3), 22–28.
4. Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. The Quarterly Journal of Economics, 116(1), 261–292. https://doi.org/10.1162/003355301556400
5. Bikhchandani, S., & Sharma, S. (2001). Herd behavior in financial markets. IMF Staff Papers, 47(3), 279–310. https://doi.org/10.2139/ssrn.864145
6. Brealey, R. A., Myers, S. C., & Allen, F. (2011). Principles of corporate finance (10th ed.). McGraw-Hill/Irwin.
7. Buckley, J. J. (1987). The fuzzy mathematics of finance. Fuzzy Sets and Systems, 21(3), 257–273. https://doi.org/10.1016/0165-0114(87)90010-8
8. Buehler, R., Griffin, D., & Ross, M. (1994). Exploring the "planning fallacy": Why people underestimate their task completion times. Journal of Personality and Social Psychology, 67(3), 366–381. https://doi.org/10.1037/0022-3514.67.3.366
9. Chapman, C. (2006). Project risk management: What is the best way to manage uncertainty? International Journal of Project Management, 24(5), 365–374. https://doi.org/10.1016/j.ijproman.2006.02.003
10. Chen, C. T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets and Systems, 114(1), 1–9. https://doi.org/10.1016/S0165-0114(98)00377-1
11. Deng, X., & Hendry, L. C. (2017). Incorporating behavioral aspects in fuzzy decision support systems: The case of overconfidence in investment decisions. Expert Systems with Applications, 80, 206–216. https://doi.org/10.1016/j.eswa.2017.03.059
12. Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383–417. https://doi.org/10.2307/2325486
13. Huang, X. (2006). Portfolio selection with a new definition of risk. European Journal of Operational Research, 170(1), 254–266. https://doi.org/10.1016/j.ejor.2004.06.016
14. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185
15. Kahraman, C., Cebeci, U., & Ulukan, Z. (2003). Multi-criteria supplier selection using fuzzy AHP. Logistics Information Management, 16(6), 382–394. https://doi.org/10.1108/09576050310503367
16. Lather, A. S., Jain, S., & Anand, S. (2020). The effect of personality traits on cognitive investment biases. Journal of Critical Reviews, 7(2), 221–229.
17. Levin, I. P., Schneider, S. L., & Gaeth, G. J. (1998). All frames are not created equal: A typology and critical analysis of framing effects. Organizational Behavior and Human Decision Processes, 76(2), 149–188. https://doi.org/10.1006/obhd.1998.2804
18. Li, R. & Tzeng, G. H. (2009). Identification of a threshold value for the DEMATEL method: Application to market segment evaluation. International Journal of Production Research, 47(14), 3771–3788. https://doi.org/10.1080/00207540701769983
19. Menon, M., Huber, R., West, D. D., Scott, S., Russell, R. B., & Berns, S. D. (2023). Community-based approaches to infant safe sleep and breastfeeding promotion: A qualitative study. BMC Public Health, 23(1).
20. Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77–91. https://doi.org/10.2307/2975974
21. Pamučar, D., &Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). Expert Systems with Applications, 42(6), 3016–3028. https://doi.org/10.1016/j.eswa.2014.11.057
22. Ryan, P., & Ryan, G. (2002). Capital budgeting practices of the Fortune 1000: How have things changed? Journal of Business and Management, 8(4), 355–364.
23. Sahi, S. K., Arora, A. P., & Dhameja, N. (2013). An exploratory inquiry into the psychological biases in financial investment behavior. Journal of Behavioral Finance, 14(2), 94–103. https://doi.org/10.1080/15427560.2013.790387
24. Shefrin, H. (2007). Behavioral corporate finance: Decisions that create value. McGraw-Hill/Irwin.
25. Statman, M. (2010). What investors really want: Know what drives investor behavior and make smarter financial decisions. McGraw-Hill Education.
26. Sunstein, C. R. (2000). Behavioral law and economics. Cambridge University Press.
27. Thaler, R. H. (1999). Mental accounting matters. Journal of Behavioral Decision Making, 12(3), 183–206. https://doi.org/10.1002/(SICI)1099-0771(199909)12:3<183::AID-BDM318>3.0.CO;2-F
28. Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. Science, 185(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124
29. Van Laarhoven, P. J. M., & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. Fuzzy Sets and Systems, 11(1-3), 229–241. https://doi.org/10.1016/S0165-0114(83)80082-7

30. Yalçın, N., Bayrakdaroglu, A., & Kahraman, C. (2012). Application of fuzzy multi-criteria decision-making methods for financial performance evaluation of Turkish manufacturing industries. Expert Systems with Applications, 39(1), 350–364. https://doi.org/10.1016/j.eswa.2011.07.024
31. Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X
32. Zhou, H., Guo, H., & Li, Y. (2020). Modeling dynamic investment decisions using fuzzy Bayesian networks considering behavioral factors. Computers & Industrial Engineering, 149, 106824. https://doi.org/10.1016/j.cie.2020.106824