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Abstract: *Both fuzzy optimization and behavioral finance have made important contributions to the field of portfolio selection on their own. Although behavioral finance emphasizes how cognitive biases like herding, anchoring, and overconfidence affect investment choices, fuzzy linear programming (FLP) has gained popularity as a way to handle uncertainty and conflicting goals in portfolio optimization. Even though each field of study is expanding, little is known about how behavioral biases can be incorporated into fuzzy optimization frameworks. This study suggests a novel behavioral fuzzy linear programming (BFLP) model that uses fuzzy representations of return expectations, risk perceptions, and allocation preferences to incorporate important behavioral biases into the portfolio selection process. The study looks into whether taking these biases into consideration impacts how optimal portfolio choices are. This study evaluates the degree to which psychological distortions affect portfolio composition and performance under uncertainty by contrasting the outcomes of the BFLP model with a conventional bias-neutral FLP model.*

Introduction:

It is anticipated that the results will aid in the creation of optimization models that are more realistic and behaviorally based, with useful ramifications for behavioral economists, portfolio managers, and investors. This combined strategy offers a strong framework for making decisions that takes into account both the limited rationality of investors and the fuzziness of financial markets.

Conventional financial theories, like the Modern Portfolio Theory (MPT) and the Efficient Market Hypothesis (EMH), are predicated on the idea that investors are logical beings who only make choices after objectively weighing risk and return. According to these models, financial markets are efficient and asset prices reflect all available information without any behavioral distortion (Markowitz, 1952; Fama, 1970). However, empirical observations have consistently demonstrated that investors frequently depart from rationality due to cognitive biases, heuristics, and emotions. Behavioral finance, which incorporates psychological insights into financial decision-making, emerged as a result of this discrepancy between observed behavior and theoretical rationality (Kahneman & Tversky, 1979; Thaler, 1993).

When making investment decisions, one of the main obstacles is the unpredictability of the financial markets. Macroeconomic indicators, asset prices, returns, and volatility are all prone to dynamic swings and frequently lack exact predictability. Furthermore, when building a portfolio, investors have to take into account a number of competing factors, such as optimizing

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returns, reducing risk, preserving liquidity, or meeting social responsibility goals. According to Zopounidis and Doumpos (2002), this automatically turns the portfolio selection process into a multi-criteria decision-making (MCDM) problem under uncertainty. Such ambiguity and vagueness are difficult for traditional deterministic optimization models to handle well.

Researchers and practitioners have been using fuzzy optimization techniques, especially fuzzy linear programming problems (FLPPs), more and more to deal with these uncertainties. Zadeh (1965) developed fuzzy set theory, which uses membership functions rather than discrete values to provide a mathematical framework for capturing imprecise information. When it comes to choosing a portfolio, Fuzzy linear programming allows for more flexible and realistic modeling of investor preferences, fuzzy constraints, and uncertain returns (Watada, 1997). It conforms to the linguistic and qualitative characteristics of investor judgments and takes into account the ambiguity present in financial data.

The inclusion of behavioral biases in the fuzzy optimization framework provides an enhanced viewpoint beyond data uncertainty. Investor behavior is known to be significantly influenced by behavioral patterns like the anchoring effect, herding behavior, and overconfidence bias. According to Barber and Odean (2001), overconfident investors frequently underestimate the risks involved and overestimate their capacity for prediction. Regardless of fundamentals, herding investors imitate the behavior of others, resulting in correlated investment patterns (Bikhchandani & Sharma, 2001). When people rely too heavily on past prices or preliminary estimates, it's known as anchoring. Anchoring distorts people's updated assessments when they place an undue emphasis on past prices or preliminary estimates (Tversky & Kahneman, 1974). To guarantee that portfolio models accurately represent investor reality, these biases must be taken into consideration as they drastically change the optimization logic.

It is possible to convert psychological distortions into mathematical constructs by incorporating behavioral tendencies into fuzzy LPP. Overconfidence, for instance, can be modeled by lowering the perceived range of risk or inflating the upper bound of fuzzy expected returns; herding behavior can be modelled by imposing constraints that favor popular assets; and anchoring can be introduced by establishing bounds based on historical values. This makes it possible to create behaviorally adaptive fuzzy optimization models that more accurately represent the tastes and profiles of actual investors.

This approach's primary benefit is its comprehensive depiction of investment decision-making. It blends the flexibility of fuzzy logic, the realism of behavioral finance, and the rigorousness of linear programming. These models look for portfolios that reflect the thoughts, emotions, and behaviors of real investors in the face of uncertainty rather than just those that are mathematically optimal. For both institutional and individual investors working in volatile markets, this method produces investment strategies that are more flexible, realistic, and psychologically based.

Literaure Review:

Two major research tracks have emerged in the evolution of portfolio optimization: the fuzzy optimization track, which uses soft computing techniques to model the ambiguity and uncertainty of financial data, and the behavioral perspective, which integrates psychological biases into investment decision-making. This review of the literature identifies areas of convergence and critically evaluates current research in these fields. The impact of cognitive

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biases on portfolio decisions, frequently in interrelated ways, has been examined in recent behavioral finance research. Confirmation bias, gambler's fallacy, and hot-hand fallacy were among the several biases that Ossareh et al. (2021) investigated concurrently among Tehran Stock Exchange investors. They found that biases frequently co-occur, especially among novice investors managing sizable portfolios, using PCA and k-means clustering. The study highlighted how unsupervised learning can be used to identify investor profiles based on joint biases.

In order to investigate the impact of demographics and personality traits on biases like anchoring, availability, representativeness, and mental accounting, Choudhary et al. (2021) used logistic regression with an emphasis on Indian millennial investors. Their findings showed that while gender, income, and neuroticism increased bias susceptibility, financial literacy significantly decreased it, underscoring the necessity of incorporating investor psychology into financial modeling.

This line of investigation was furthered by Kandpal and Mehrotra (2018), who showed that Indian investors' choices are more influenced by their lifestyle, financial objectives, and emotions than by dispassionate analysis. The importance of behavioral awareness in financial education was further supported by the dominance of risk aversion and liquidity preference as behavioral traits.

Wang et al. (2025) conducted a thorough analysis of overconfidence bias, a common theme in behavioral finance, and discovered that while it can occasionally improve market efficiency, overconfidence typically lowers individual performance in realistic trading environments. Overconfidence's dual nature poses a problem for optimization since it can raise expectations while jeopardizing risk management.

Jayewardene and Nanayakkara (2025) investigated the role of personality traits further and discovered that the relationship between traits such as openness and extraversion and actual investment outcomes is mediated by loss aversion. According to their structural equation modeling, some personality types either strengthen or lessen cognitive biases, which suggests that behavioral parameters might be included in optimization constraints.

In a detailed analysis of overconfidence bias, a common theme in behavioral finance, Wang et al. (2025) discovered that while overconfidence can occasionally improve market efficiency, it typically lowers individual performance in realistic trading environments. Overconfidence's dual characteristics pose a problem for optimization since they can raise expectations while jeopardizing risk management.

In their further investigation of the role of personality traits, Jayewardene and Nanayakkara (2025) discovered that the relationship between traits such as openness and extraversion and actual investment outcomes is mediated by loss aversion. Certain personality profiles either amplify or dampen cognitive biases, according to their structural equation modeling, which suggests behavioral parameters could be included in optimization constraints.

When taken as a whole, these studies show that behavioral biases are not unique occurrences. Rather, they are intricately linked to the personality traits, contextual factors, and investor demographics. It is possible to create more realistic, behaviorally based decision frameworks by incorporating such biases into fuzzy portfolio models, particularly those based on fuzzy

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LPP. Designing models that represent real investor behavior rather than theoretical rationality requires a collaborative assessment of these biases, as the literature has shown.

Models for Fuzzy Optimization in Portfolio Selection

The ability of fuzzy logic techniques to model imprecise data has made them useful in financial decision-making. To rank, prioritize, and optimize portfolios under uncertainty, fuzzy AHP and TOPSIS techniques, trapezoidal and triangular fuzzy numbers, and interval-valued fuzzy sets are commonly employed.

• A new simplex algorithm for Interval-Valued Fermatean Fuzzy Linear Programming (IVFFLP) was presented by Bihari and Kumar (2025). This algorithm is appropriate for real-world uncertainties like resource allocation and transportation.

• Huang et al. (2025) used piecewise linear functions to apply fuzzy expected returns based on economic transitions, letting investor sentiment influence asset selection.

In order to account for investor risk attitudes in return projections, Zhang et al. (2025) presented a machine learning-enhanced fuzzy model that uses LSTM and SVR.

Nath et al. (2025) employed interval-type fuzzy sets in a multi-objective programming model that included objectives such as capital growth, liquidity, and dividend yield for actual data from Indian exchanges.

Behavioral Elements in the Optimization of Portfolios

Several cognitive biases that result in irrational investment behavior have been identified by behavioral finance literature:

• According to Barber and Odean (2001), overconfidence causes people to overestimate returns and underestimate risk.

• Especially in times of uncertainty, herding influences correlated decision-making (Bikhchandani & Sharma, 2001).

• When predicting future asset performance, anchoring results in a dependence on past data or preliminary projections (Tversky & Kahneman, 1974).

Research indicates that these biases are common among retail investors, especially in emerging markets (Choudhary et al., 2021; Robin & Angelina, 2020). However, there aren't many models that quantitatively incorporate these biases into optimization formulations.

3. Integrated Decision Frameworks and Hybrid Models

Numerous studies investigated hybrid frameworks that combined soft computing tools, MCDM, and fuzzy models:

• Aggarwal et al. used MSBM-TOPSIS to rank portfolios according to risk-return profiles in a fuzzy environment.

• Sharma (2025) combined Boruta-GA and Trapezoidal Bipolar Fuzzy VIKOR to improve decision-making in big data scenarios.

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• Using fuzzy inference rules and technical indicators, Khan et al. (2024) suggested a trading system based on fuzzy rules.

• To increase the stability of stock selection, Lakshmi & Kumara (2024) integrated fuzzy AHP and TOPSIS with sensitivity analysis.

These studies support the viability of MCDM tools in portfolio construction but typically lack direct behavioral modeling.

Research Gap and Future Direction

Although behavioral biases and fuzzy modeling are covered separately in previous research, it is uncommon to find an integrated model that combines the two. The majority of fuzzy models overlook the dynamic, psychological aspect of decision-making by assuming constant investor preferences or general risk attitudes.

The suggested course of action Present a model for behaviorally-informed fuzzy linear programming (BFLP):

Fuzzy membership functions can be adjusted for risk and returns using behavioral data, such as survey-based Likert scores.

• Use fuzzy allocation constraints to model herding, giving preference to popular assets.

• Using fuzzy bounds based on past investment trends, introduce anchoring.

By contrasting BFLP with conventional FLP models, it is possible to assess how these changes affect expected return, optimal portfolio composition, and fuzzy satisfaction metrics.

Conclusion:

Due to the increasing impact of fuzzy optimization techniques and behavioral finance, the field of portfolio optimization has undergone significant change. Although there is a great deal of research in both areas—fuzzy multi-criteria decision-making (MCDM) techniques in uncertain financial environments and behavioral biases in investment decision-making—these two streams have hardly ever been combined into a single optimization framework.

By integrating three major behavioral biases—overconfidence, herding, and anchoring—into a fuzzy linear programming (FLP) model for portfolio optimization, this study suggests a fresh approach. The main goal is to examine whether behavioral distortions affect the best way to allocate stocks in comparison to a conventional bias-neutral fuzzy LPP model. The model attempts to replicate actual investor behavior by incorporating psychological patterns into fuzzy parameters like return expectations, risk assessments, and allocation preferences in more realistic way.

The suggested study has a number of noteworthy benefits.

• It aligns investor irrationalities with optimization techniques, bridging the gap between mathematical rigor and psychological realism.

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• By addressing subjective human factors that traditional models overlook, it improves the relevance of fuzzy LPP models.

• The model is adaptable and can be adjusted to suit various market conditions and investor profiles by adjusting fuzzy parameters appropriately; it allows for a comparison of rational and behaviorally-informed models, providing insights into how behavioral biases alter optimal investment outcomes.

But the strategy has some drawbacks as well:

• It may be necessary to use surveys, subjective judgment, or assumptions to quantify behavioral biases into fuzzy sets, which could result in estimation errors.

• Because behavioral influences are context-sensitive and dynamic, static fuzzy constraints may not adequately capture real-time decision shifts.

• Large-scale surveys or psychological profiling, which can be resource-intensive, may be necessary for data collection in order to accurately measure behavioral tendencies.

• Fuzzy model calibration with behavioral inputs is not standardized and may require iterative improvement.

The suggested integration has a lot of potential for both academic and real-world application, despite these obstacles. It enables investors and researchers to examine whether adding behavioral traits to a portfolio under uncertainty results in noticeably different or better outcomes. If successful, this hybrid model might change portfolio theory by bringing in a more human-centered optimization methodology.

In the end, this research aims to redefine what "optimal" actually means when human behavior, uncertainty, and mathematical rigor intersect, rather than merely identifying optimal portfolios. Future research can improve the model even more by adding dynamic market signals, adaptive behavioral weights, and sophisticated AI-based methods for fuzzy inference and behavioral profiling.

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