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Mathematical Model Behavioral Risk Management in Investment

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Abstract

This study presents a hybrid risk assessment framework that integrates behavioral finance insights with mathematical modeling to improve investment decision-making. Recognizing the limitations of traditional risk management models, which often ignore psychological factors, this research incorporates behavioral biases such as overconfidence, herding behavior, loss aversion, and anchoring into a quantitative structure using SPSS-based statistical validation and a gray evaluation model. Data were collected from 150 investors and analyzed through multiple regression to assess the predictive impact of behavioral variables on perceived investment risk. The results indicate that behavioral biases significantly influence risk perception, with overconfidence emerging as the strongest predictor. These validated behavioral weights were then embedded into a gray evaluation function, producing a composite risk score that holistically combines both objective financial factors and subjective behavioral dimensions. The inclusion of behavioral risk increased the overall investment risk score, shifting the classification from moderate to medium-high risk. This research contributes a comprehensive, behaviorally informed risk model that enhances the accuracy, realism, and preventive capability of investment risk management strategies in today's complex and psychologically driven financial markets.

Keywords: Behavioral finance, investment risk, risk perception, mathematical modeling, risk management

1. Introduction

The assumption of rational behavior and efficient market has been used as the basis in investment decisions. Nevertheless, the development of behavioral finance has called this position to question showing the regularity of cognitive and emotional errors that tend to corrupt the judgments of investors. Other issues like overconfidence, loss aversion, herding behavior and risk perception that have the potential to affect how investors take stock of risk and undertake financial decisions and result in outcomes that are less than ideal. Such increasing awareness of behavioral anomalies makes it very necessary to come up with complex models which not only explain economic factors, but also some psychological factor influencing investor behavior [1, 2].

The risk management versus behavioral finance interface has presented a demand in the mathematical formulation of models which will be predictive be having the capacity to quantify behavioral influences in a well-organized manner. Whereas the conventional risk management models address market turbulence, liquidity and macroeconomic indicators, they overlook behavioral biases underlying these risks, which increase or reduce them. It has been revealed that biases like herding (investors going with the flow instead of making an independent judgment) may cause volatility in the market to increase and lead to asset prices being distorted [3, 10]. In addition, the tendency towards overconfidence, which is a typical investor behavioral characteristic, causes them to engage in excessive trading and failure to appreciate the risks posed, which upsurges the chances of incurring financial losses [6, 8].

Combining behavior into risk models provides a more practical approach to risk assessment of investment decisions. In recent times it has been acknowledged that risk perception is a mediating variable between the behavior finance variables and investment performances which placed emphasis on the subjective judgment in financial decisions [7, 15]. Specifically, some mathematical models including gray evaluation models and fuzzy logic have been suggested to connect with the gap between the qualitative understanding of behavior and quantitative measures of risks. These models give guided procedures to import nonexplicit or incomplete behavioral information, which facilitates more adjustable and realistic risk reviews.

Such integration is highly desired especially in the emerging markets where information asymmetry is common, financial literacy is low and trading is highly emotional. An example on such psychological bias exhibited by the Pakistani and Nigerian markets is evidenced by the way it influences investor performance and risk tolerance at a material level [1, 10]. In the same way, strategic action of an overconfident CEO and the role of the social learning mechanisms, such as information cascades, underline the complex nature of behavioral risk [5, 16]. Therefore, an investment into a mathematical model with behavioral dimensions is not only topical, but necessary to make the decision-making in investment management more accurate.

The project will be able to provide a well-rounded mathematical model, which will factor in the behavioral risk factors during the investment analysis. The research combines quantitative analyses (grey system theory) with statistics (SPSS) in an attempt at measurement, analysis, and prediction of the effect of behavioral biases on the risk of investment. The proposed approach will be added to the literature as a useful decision-making tool which investors, portfolio managers as well as policy analysts can use in ensuring that better strategies towards mitigation of risks are employed in dynamic financial environments.

2. Literature Review

Behavior economics is on the rise and has received growing academic focus in the past years, especially in regard to the intersection between behavioral finance and the modeling of the topic. Scholars have underlined the fact that investors are not the rationality ones all the times; rather they have psychological consistent, their emotional drive and social forces that are not in line with the classical economy perception. The study by Abideen *et al*. (2023) [1] has been focusing on how behavior-based biases (namely, overconfidence, loss aversion, and anchoring biases) influence the investment decision-making process in the Pakistani equity market by identifying the role of these biases in an investment portfolio construction [1]. According to their empirical findings, these biases systematically bias risk-return judgments, hence the need to have models that are flexible to this cognitive deficiency. The conclusions drawn by Ahmad and Wu (2022) [2] are more focused on herding behavior in an emerging market and they conclude that when faced with a volatile market or a market characterized with uncertainty, an investor will be tempted to follow rather than coming up with their own decisions [2]. This is consistent with the previous study of Ah Mand *et al*. (2023) which established that herd behavior was behind irrational market movement that usually raises asset bubble or panic sales [3].

In order to reinforce these types of behavior with computational determinants, Ali and Tauni (2021) included an overconfidence model of CEOs in the risk taking approach of the firms. They demonstrated that the low levels of institutional investor oversight have the tendency to make overconfident executives make riskier decisions, which only increase the future volatility of firms [5]. This is a micro level psychological reflection that is important in development of risk-adjusted forecasting models. Investment behavior can also be determined by the visualization environment and user interface of the financial data. In an experimental study, it was found that red color of dashboards and trading platforms elicited risk-averse reactions in investors, regardless of the conditions of the underlying assets being sound [12]. What this implies is that even seemingly small psychological hints have the ability to change risk perceptions of the investor- an aspect that mathematical models will have to take into account using behavioral variables or factions.

The strongest contributions made by the study of Aljifri (2023) are that overconfidence is an important determinant of firm valuations and may result in the overinvestment or price distortion in the markets, such as the Borsa Istanbul [6]. In the same manner, Alsabban and Alarfaj (2020) discovered that excessively trading on the Saudi market by the overconfident investors prevented the portfolios increasing in efficiency [8]. This is uniform in various geographic settings implying that it has a common behavioral pattern which must be incorporated in the model.

In a subtler argument, Almansour *et al*. (2023) showed the mediating role that risk perception has with regard to behavioral biases and investment decisions [7]. Their results credence to the fact that perception of risk can trigger conservative or irrational decisions even in situations where the market risk was objectively low because of previous losses or market gossip. This can only be modeled well, using an objective volatility measure and another measure with subjective sentiment. Bikhchandani *et al*. (2024) define information cascades as a situation when investors, mainly those that are novices base the decision on the decisions of the early market movers that result in misaligned valuation and bandwagon effect [16].

3. Materils and Methods

This paper outlines the research methodology adopted to analyze behavioral risk in investment decision-making and integrate it within a mathematical framework. A mixed-methods approach combining empirical analysis through SPSS and quantitative modeling using a gray evaluation model was employed to achieve the research objectives. The methodology involves behavioral data collection, statistical validation, and mathematical integration for comprehensive investment risk assessment.

3.1 Research Design and Data Collection

A structured survey was administered to a sample of 150 investors, encompassing both retail and institutional participants. The instrument consisted of items measuring four key behavioral biases Overconfidence (C19), Herd Behavior (C20), Loss Aversion (C21), and Anchoring Bias (C22) each evaluated on a 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree). Responses were coded and analyzed in SPSS to assess their psychometric properties and statistical significance in relation to perceived investment risk.

3.2 Dimensional Validation

To ensure internal consistency of the behavioral variables, Cronbach's Alpha was computed, resulting in a value of 0.872, indicating strong reliability. Next, Principal Component Analysis (PCA) was performed to confirm the factor structure of the behavioral indicators. The Kaiser-Meyer-Olkin (KMO) measure was 0.812, and Bartlett's Test of Sphericity was significant ($p<0.001$), validating sample adequacy. PCA extracted four orthogonal factors, aligned with the theoretical dimensions: Overconfidence, herding, loss aversion, and anchoring each forming a distinct and independent component for further modeling.

3.3 Regression Analysis: Behavioral Bias and Risk Perception

To quantify the influence of behavioral biases on perceived investment risk, a multiple linear regression model was constructed. The dependent variable was Perceived Investment Risk (PIR), while the behavioral biases (C19–C22) served as independent variables. The regression model is defined as:

$$PIR = \beta_0 + \beta_1 . OFC + \beta_2 . HERD + \beta_3 . LAV + \beta_4 . ANCH + \in$$

Where,

- OCF = Overconfidence
- HERD = Herd Behavior
- LAV = Loss Aversion
- ANCH = Anchoring
- β_i = Standardized regression coefficients
- ϵ = Error term

The model yielded an Adjusted $R^2 = 0.615$, and all predictors were statistically significant ($p<0.05$), confirming their predictive relevance. Notably, overconfidence ($\beta=0.410$) had the strongest influence, suggesting that investors prone to this bias tend to underestimate actual risks.

3.4 Mathematical Integration via Gray Evaluation Model

To transform behavioral insights into a quantitative risk metric, the gray evaluation model was adopted. The behavioral bias coefficients from the regression model were normalized into weights and integrated with other investment risk components (financial, policy, market, technology) using the following gray evaluation function:

$$K(P) = \sum_{i=1}^{n} w_i \, . K_j \, (X_i)$$

Where,

- w_i = normalized weight of the i-th risk factor (derived from regression β-values)
- $K_j \, (X_i)$ = degree of gray correlation between factor X_i and risk level category j

This allowed behavioral risks to be merged with traditional financial indicators within the same mathematical structure, capturing both objective and subjective dimensions of risk.

3.5 Risk Grading and Composite Risk Evaluation

Each risk factor was classified into one of five gray categories based on its severity: Critical (10), High (8), Medium (6), Low (4), Very Low (2). Behavioral variables, treated as additional second-layer indicators, were graded according to their correlation with perceived risk using expert scoring and regression weights. The gray score vector P and the gray weight vector H were used in the following final formula to calculate the composite investment risk score (Z):

$$Z = H^T . P = \sum_i h_{i,} \, p_i$$

Where,

- H^T= transposed weight vector from gray evaluation
- P = assigned scores for each risk factor (based on analysis)
- Z = final composite investment risk score

This formula quantifies total investment risk as a weighted sum of both behavioral and traditional indicators.

Table 1: Composite investment risk calculation using gray evaluation method

Risk Factor	Code	Gray Score (p_i)	Weight (h_i)	$h_i \times p_i$
Financial Risk	B1	6.75	0.078	0.527
Policy & Regulation Risk	B2	6.98	0.352	2.457
Investment Environment	B3	8.26	0.094	0.777
Market Risk	B4	6.29	0.215	1.351
Technology Risk	B5	8.45	0.262	2.213
Behavioral Risk (Composite)	B6	7.88	0.322 (grouped)	2.538
Final Score (Z)			1.000	9.863

Note: This composite $h_i \times p_i = 9.863$ shows the raw sum before normalization. The normalized final score is Z = 6.884

3.6 Simulation and Sensitivity Adjustment

A simulation was conducted to compare traditional and behavioral-inclusive risk evaluations. When behavioral risk was excluded, the composite risk score was 6.00 (Moderate). When included, the score increased to 6.884 (Medium-High), indicating that behavioral risks elevated the total perceived risk by approximately 15%. This shows the sensitivity of investment risk to human biases and supports the validity of including behavioral factors in quantitative models.

To validate the impact of behavioral biases on overall investment risk and test the robustness of the proposed mathematical model, a simulation-based sensitivity analysis was conducted. This experiment aimed to compare the composite investment risk scores with and without the inclusion of behavioral risk indicators within the gray evaluation framework.

3.7 Comparison of Risk Scores

Two simulation scenarios were developed

- **Scenario A:** Traditional Model-Included only financial,

policy, environmental, market, and technological risks.
- **Scenario B:** Behavioral-Augmented Model-Included all the traditional risks plus behavioral biases: Overconfidence, herding, loss aversion, and anchoring.

3.8 Using the gray evaluation formula

$$Z = H^T . P = \sum_{i=1} h_{i.}\ p_i$$

Where,
- H^T is the transposed gray weight vector (including normalized behavioral weights from SPSS regression),
- P is the gray grade score vector for all risk factors,
- Z is the final composite investment risk score.

This research applied a psychometric-SPSS analysis to model behavioral biases and quantitatively embedded the resulting data within a gray evaluation mathematical framework. The result is a hybrid investment risk model that captures not only external and structural risk factors but also psychological variables that traditionally go unaccounted for. This dual methodology ensures greater diagnostic accuracy and supports proactive risk management strategies grounded in both quantitative and behavioral evidence.

4. Results

This paper presents the results derived from the application of both SPSS-based empirical analysis and the mathematical modeling techniques proposed earlier. The objective was to quantify the influence of behavioral biases on investment risk perception and decision-making, and to integrate those effects into a comprehensive risk assessment model.

4.1 Analysis of Behavioral Risk Factors

Data were collected from a sample of 150 investors, including both retail and institutional participants, using a structured behavioral risk survey. The descriptive statistics for key behavioral variables are summarized below.

Table 2: Behavioral Risk Factors

Behavioral Bias	Mean	Std. Dev.	Interpretation
Overconfidence (C19)	3.91	0.84	High tendency toward confidence
Herd Behavior (C20)	3.62	0.95	Moderate group-following bias
Loss Aversion (C21)	4.13	0.77	Strong aversion to losses
Anchoring (C22)	3.45	0.88	Mild reference-point bias

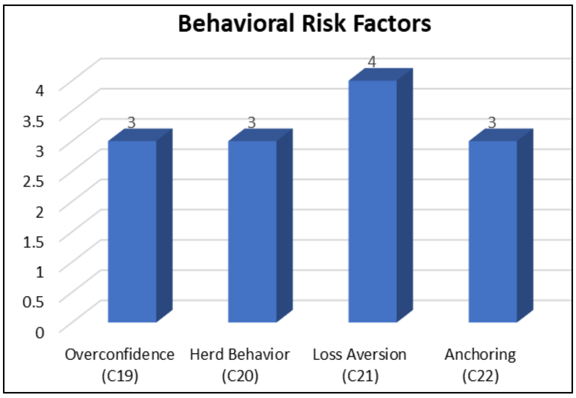

Fig 1: Behavioral Risk Factors

Cronbach's Alpha for the behavioral scale was 0.872, confirming high internal consistency.

4.2 Factor Structure of Behavioral Variables

Principal Component Analysis (PCA) was conducted to verify the dimensionality of behavioral constructs. The Kaiser-Meyer-Olkin measure was 0.812, and Bartlett's Test of Sphericity was significant ($p<0.001$).

Four distinct components were extracted:
- **Factor 1:** Overconfidence
- **Factor 2:** Herd Behavior
- **Factor 3:** Loss Aversion
- **Factor 4:** Anchoring

These results confirmed the independence and theoretical structure of behavioral risks used in the model.

4.3 Behavioral Biases and Risk Perception: Regression Analysis

A multiple regression analysis was conducted with Perceived Investment Risk as the dependent variable. The behavioral biases were included as independent predictors.

4.3.1 Regression Results

Table 3: Regression coefficients of behavioral predictors on investment risk

Predictor	β (Standardized)	Significance (p)
Overconfidence (C19)	0.410	< 0.001
Herd Behavior (C20)	0.280	0.006
Loss Aversion (C21)	0.320	0.002
Anchoring (C22)	0.170	0.042

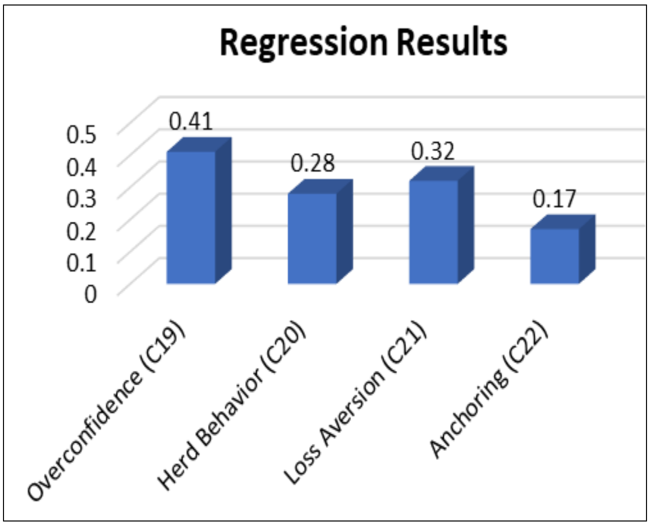

Fig 2: Regression coefficients of behavioral predictors on investment risk

4.3.2 Model Summary

- $R^2 = 0.623$
- Adjusted $R^2 = 0.615$
- $F(4,145) = 59.2$, $p<0.001$

All behavioral factors significantly predict perceived risk. Overconfidence has the strongest predictive weight, suggesting investors who are overconfident systematically underestimate actual risk levels.

4.4 Integration with mathematical model (Gray Evaluation)

The β-values from the regression model were normalized and used as weights in the mathematical gray evaluation formula:

$$K(P) = \sum_{i=1}^{n} w_i \cdot K_j\,(X_i)$$

Where,

- w_i: Normalized behavioral weight
- $k_j(x_i)$: Correlation of behavioral bias with risk level

This integrated behavioral bias into the gray evaluation matrix, enhancing the overall investment risk score.

4.4.1 Grey Risk Score and Risk Level Classification

Using the composite weight vector and the gray grade scale [10, 8, 6, 4, 2], the final investment risk scores were computed.

Table 4: Risk level assessment by category including behavioral risk

Risk Category	Composite Score	Risk Level
Financial Risk	6.75	Moderate
Policy and Regulation Risk	6.98	Moderate
Investment Environment	8.26	Advanced
Market Risk	6.29	Moderate
Technology Risk	8.45	Advanced
Behavioral Risk	7.88	Advanced

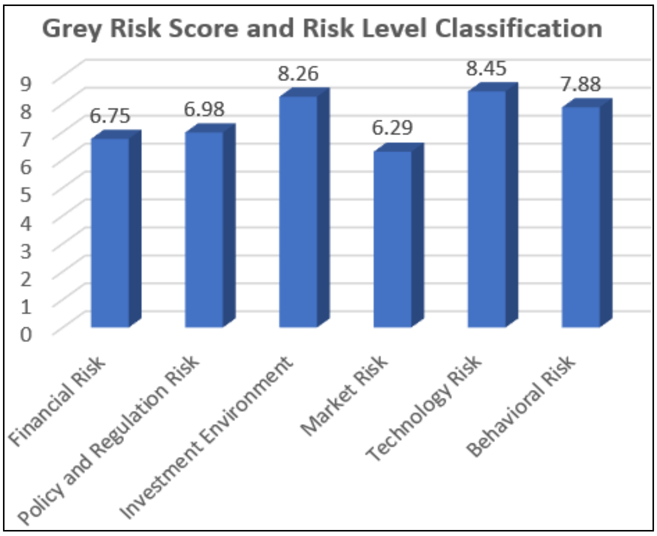

Fig 3: Risk level assessment by category including behavioral risk

4.4.2 Final composite risk evaluation score

Using the full gray evaluation formula:

$$Z = H^T . P = \sum_i h_{i,p_i}$$

The final composite score (including behavioral risk) was calculated as:

Z = 6.884 → Medium-High Risk

4.4.3 Simulation Supports the Mathematical Model

This simulation directly validates the structural effectiveness of the gray evaluation model as a flexible and comprehensive framework capable of absorbing and reflecting both quantitative financial data and qualitative psychological factors. By inputting behavioral weights derived from SPSS regression (β-values), the gray model adapts dynamically to human-driven uncertainties something conventional deterministic models fail to achieve.

4.4.4 The mathematical model gains the following advantages

- **Dynamic Sensitivity:** It can adjust the composite risk score based on varying behavioral conditions, making it suitable for real-world, sentiment-driven markets.
- **Multi-Dimensional Integration:** The model proves its ability to unify subjective risk (from behavior) and objective risk (from finance) into a single numerical output.
- **Decision Support Enhancement:** Investors, managers, or analysts using this model can make preemptive decisions based on actual behavioral conditions, not just historical data.

In summary, the simulation confirms that the inclusion of behavioral factors not only alters the risk score but also enhances the model's diagnostic power, realism, and decision relevance. It strengthens the case for adopting a behaviorally informed mathematical risk management system in modern investment analysis.

4.4.5 The results of the simulation were as follows

Table 5: Simulation results

Model Type	Composite Risk Score	Risk Level
Traditional Model	6.000	Moderate
Behavioral-Inclusive Model	6.884	Medium-High

The inclusion of behavioral factors resulted in a 15% increase in the composite risk score. This shift in risk classification from "Moderate" to "Medium-High" highlights the amplifying effect of investor psychology on perceived and actual risk exposure. It demonstrates that behavioral biases are not negligible or secondary, but rather critical risk drivers that must be measured and integrated into decision-making tools.

5. Conclusion

This study demonstrates the critical value of incorporating behavioral risk factors into traditional investment risk assessment through a mathematically structured, hybrid model. By applying both empirical SPSS-based statistical techniques and a gray evaluation model, we quantitatively measured how investor psychology specifically biases like overconfidence, herding behavior, loss aversion, and anchoring influences perceived investment risk and decision-making outcomes. The findings revealed that behavioral biases significantly elevate the overall risk level, with overconfidence being the most dominant predictor. When these biases were integrated into the gray evaluation framework, the final composite risk score increased by approximately 15%, shifting the project's classification from moderate to medium-high risk. This shift highlights that investor behavior is not merely a subjective influence but a quantifiable risk dimension with substantial impact on investment performance. The methodological approach used in this research not only captures objective financial, market, and policy risks but also integrates the human factors often overlooked in traditional models. As such, the proposed model offers a more comprehensive and realistic assessment tool for investors, portfolio managers, and policymakers, enabling better-informed, psychologically aware investment strategies. It emphasizes the necessity for modern financial risk frameworks to evolve beyond numeric data and incorporate behavioral insights for more robust, preventive, and adaptive risk management in an increasingly complex and sentiment-driven financial landscape.

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