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RPLR -ASBO- A novel model of risk communication and risk perception in financial decision making

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ABSTRACT

The interaction between risk communication and risk perception plays a pivotal role in shaping financial decision-making, particularly in complex investment environments. Traditional financial advice often emphasizes assessing clients' risk tolerance while overlooking how the communication of risk information influences clients' perception of potential losses and uncertainties. The analysis examines the effectiveness of conveying financial risks in the perception of risk by investors and thus their decisions to invest. This analyzed on the direct and indirect effects of risk education on allocation to risky assets based on risk perception based on survey respondents of 465 financial adviser clients. The respondents were asked to complete structured questionnaires on risk communication quality (RCQ), risk perception (RP), investment choice (IC), Emotional Response to Risk (ERR) and Information Seeking Behavior (ISB). SPSS version 27 was used to analyze the data, and regression, correlation, and descriptive statistics were used to investigate associations between the variables. The results indicate that the Clear risk communication (b = 0.420, r = 0.52) contributes to the financial decision-making, the most help of risk perception (b = 0.310) and investment choices (b = 0.365) and moderate effects of emotional response (b = 0.180) and information seeking behavior (b = 0.250). In addition to this, the study proposed Risk Perception using Logistic Regression (RPLR) based Adaptive Satin Bowerbird optimization (ASBO) model for analyzing the risk communication and risk perception. Risk communication significantly impacts financial decisions, with clarity of communication boosting decision quality. The relationship between communication and perception is confirmed in direct and indirect effects. Development and implementation of proper strategies enhance the informed decision making, risk management and investment returns.

Keywords: Risk Communication, Risk Perception, Financial Decision-Making, Investment Decisions, Financial Advisory

1. INTRODUCTION

Financial decision-making has been defined as the art of evaluating uncertain outcomes with investors weighing potential benefits against the associated risks. It is a manifestation of personal goals, rationality and the perspectives on uncertainties in changing economic circumstances [1]. The analytical thinking does not influence the decision-making process only, but also the psychological and behavioral factors, including the personal risk-taking and past experiences [2]. These are some of the factors which influence how investors feel the uncertainty and make their financial decisions in terms of the long-term and short-term [3]. Long term financial decisions are associated with financial stability. Risk must be communicated effectively and decision making must be consistent to realistic objectives and reasonable resource allocation hence survive in hostile and uncontrollable financial environments [4]. Risk communication helps investors to learn about financial risks and it influences their judgments and decision making. It is meant to be explicit, clear and context specific to facilitate sufficient understanding [5]. This process of essentializing complex financial concepts without distorting them will help the investor to look at the uncertainties in a realistic way so that they can make rational decisions [6]. The advisers convert both technical and practical risks and this builds trust and knowledge. Good communication helps the investors to transact with opportunities with confidence and deal with financial uncertainties [7]. Risk perception describes how one perceives the uncertainty subjectively based on the experiences, emotions, and mental bias [8]. It guides investment preferences and responses to financial uncertainty. Attitudes such as fear, optimism, and the willingness to accept risk led to differences in decision-making even with identical information [9]. Accurate risk perception supports rational decision-making and sound financial choices, promoting confidence and informed investment behavior [10]. Misperception can lead to overconfidence, critically affecting investor behavior and potentially resulting in suboptimal financial decisions [11].

Earlier research often focused on either risk communication or risk perception separately, examining their interactive effect on financial decision-making. Many researches relied on hypothetical scenarios rather than real investor behavior. The present research examines both risk communication and perception simultaneously, using survey data from actual financial adviser clients. It measures direct and indirect effects on investment decisions, providing practical insights into investor behavior. The approach ensures a realistic, evidence-based understanding of under uncertainty. This investigation investigates the impact of risk communication on investors' financial choices. It aims at tracking how the relationship is mediated through risk perception. It is evoking the impression of communication interaction in an attempt to enhance the investment outcomes. The contribution of this study are:

1. The analysis presents a comprehensive model showing how effective risk communications influences investors' ability to perceive risks accurately and make informed investment decisions.
2. The empirical analysis will imply the analysis of the survey outcomes of the 465 customers of a financial advisor and the direct and indirect effects of risk communication on risky-asset allocation based on the use of descriptive statistics, correlation analysis, and regression analysis.
3. The results provide that the effectiveness of transparent and clear risk communications including contextual framing is partially mediated by the risk perception that significantly enhances the quality of investment choices and risky asset allocation.
4. Results offer useful insights that can be adopted by financial advisers to institute measures that improve the perception and handling of financial risks by clients to enable them to make more informed investment decisions.

The research is divided into the following parts: Section 1 introduces the research; Section 2 examines the literature on the subject. The conceptual framework and hypotheses are introduced in Section 3. In section 4, the methodology is described, including the survey design and the analysis with descriptive statistics, correlation,

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and regression. Section 5 covers the discussion of the results, and Section 6 discuss with conclusion, practical implications, and future research directions.

2. RELATED WORKS

The effects of overconfidence on individual investors' performance and decision-making, as well as the moderating influence of financial literacy and the mediating effect of risk perception, were investigated [12]. Research using deductive, cross-sectional, individual investor questionnaires; correlation, regression to assess mediation and moderation was used. Findings indicate that Risk perception mediates the impact of overconfidence in investment decision making and performance completely and that financial literacy moderates such relationships, enhancing the quality of decisions. Limitations Involved only a single emerging market was studied, which is a relatively small sample. The research examined cyber situation awareness in the Swedish financial sector, determining some of the information requirements of a common operational picture and understanding of cyber-threats [13]. Information was gathered through surveys and interviews with players in the sector in the process of a national crisis management exercise and compared with available theory. The results indicate good crisis management behavior and a lack of systematic examination of rational adversaries. Cyber personnel should be recommended to integrate into crisis teams. The corporate social and environmental performance (ESG) affected the risk perception and possible risk of markets to investors in the case of a public company, which was examined [14]. The research was based on five-year longitudinal research of 222 S&P-listed companies (2014-2018), depending on ESG-based measurement of corporate financial risk and measurement of a double risk. The results suggest that investor uncertainty and broader systematic risk associated with ESG performance were higher, especially in environmental scores; a potential drawback was that it is restricted to listed companies, which might influence the generalizability. Table 1 shows the overview of the literature review.

TABLE 1
Summary of Selected Studies with Key Insights.

Ref	Objective	Method	Result	Limitation
Yan [15]	Test the behavioral factors present and risk perception as an intermediary on the effect on financial decision-making.	On-line survey of 270 subjects; Structural Equation Modeling, Multiple Regression Analysis and Confirmatory Factor Analysis with SPSS 26.	Perception of risk based on herding, disposition effect, loss aversion and mental accounting; overconfidence has a direct effect on decision;	One population; online survey; causes and effects confined to cross-section.
Halim and Pamungkas [16]	Learn how overconfidence, herd mentality, and risk perception affect financial choices.	Sample size 152 stock investors on Riau; Structural Equation Modeling via Smart version 3.2.9.	Decisions about investments are also positively impacted by risk perception, overconfidence,	Restricted to Riau investors; this can be limited.

			and herding behavior. .	
Mishra et al. [17]	Examine how women's financial decision-making is affected by digital financial understanding and other factors.	Sample survey of 385 female respondents to estimate associations between financial attitude (FAtt),	financial resilience intermediated the FAtt-investment relationship; predictors explained an approximate 71% variance.	In India, restricted to 385 respondents, the results may not be applicable.
Zhang [18]	Improve financial management and investment decision-making by designing and developing a financial data analytics system.	Financial Data Company: An Analysis of financial data with the help of Hadoop and Spark as the data processing systems.	The system improved data processing speed and accuracy (98.9%), increased user satisfaction,	Limited to one company; performance might not apply to other industries.
Bu [19]	Create a fuzzy decision support system (FDSS) to optimize financial management, resource allocation, and decision making in businesses.	FDSS with microservices architecture is an architecture that integrates uncertainty fuzzy logic to optimize decision rules and decision parameters; it was appraised with empirical research at Blue Ocean Technology Co., Ltd.	Enhanced risk warning, budget management, and investment decision-making effectiveness.	Focused on a single company; implementation complexity may limit scalability.
Wu [20]	Explore how behavioral, psychological, affect financial decision-making.	Application of partial least squares method in structural equation modeling to a structured questionnaire involving 634 investors.	Financial digital literacy, financial capability, financial autonomy, and impulsivity are important elements in financial decision-making	Findings within a given community or survey participant cluster may or may not survive global generalization.

2.1 RESEARCH GAP

Earlier research investigated risk perception of COVID-19 [12], cyber situation awareness [13], and ESG-based financial risk [14], with a limitation of each study: only short-term observations were made, systematic assessment was never conducted, and only listed companies were considered. None of them directly study how risk communication influences risk perception to affect financial decision-making. The knowledge of how communication strategy affects investor behavior in the face of uncertainty is limited by this disparity. This gap can be filled to give a clue to the management of financial risks more effectively.The research overcomes these limitations by examining how risk communication directly shapes risk perception and

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investment decisions. It uses survey data from actual investors and provides practical insights into behavior under financial uncertainty.

2.2 Variable definition

The analysis includesreflection of five key variables including Risk Communication Quality (RCQ), Risk Perception (RP), Investment Choices(IC), Emotional Response to Risk (ERR), and Information Seeking Behavior(ISB). These variables are the consequences of communication on perception, emotion, information behavior and financial decision-making.

Risk Communication Quality (RCQ): It can be described as the clarity, transparency and contextual framing of financial risk reporting to investors and directly affects how investors can interpret the probability of incurring a loss. High RCQ improves decision-making process because it affects the inner perception and attitude of the investor towards the financial risks.

Risk Perception (RP): It includes the realization of investors of the probability and severity of loss of assets and this motivates their outrage at risky holdings. It affects perception and course of action regarding risk to be undertaken and this contributes to effects of risk awareness on investment decisions.

Investment Choices (IC): It has been defined as the channel decision, which the investors make on risky and safe sources of money. It is the result of the influence the risk communication and perception of risk have on the financial decision process.

Emotional Response to Risk (ERR): It is the emotional reaction of investors to the information on the financial risk, e.g., anxiety or confidence. The responses also affect the perception of risk towards investment decisions.

Information Seeking Behavior (ISB): It is the degree to which investors are eager to get more information to comprehend financial risks. It demonstrates the role of communication and perception in making proactive investment decisions.

3. METHODOLOGY

The analysis explores how risk communication shapes risk perception and influences investment decisions within financial decision-making. A survey of 465 financial advisers' clients was supported quantitatively. RCQ, RP, IC, ERR, and ISBwere measured using structured questionnaires. The data were analyzed with the help of descriptive statistics, correlation, and regression analyses, and the indirect effect of risk perception was tested with the help of the mediation analysis.Figure 1 illustrates the theoretical framework and connections in the analysis.

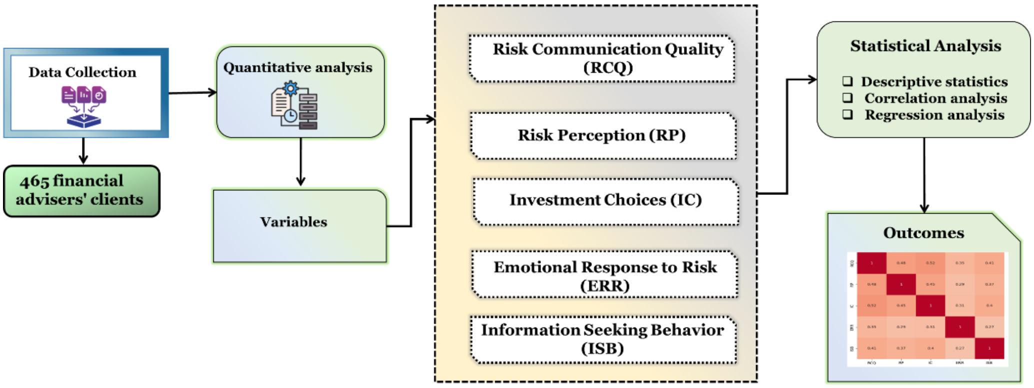

FIGURE 1: Conceptual Framework Illustrating Variables and Analysis Flow.

3.1 DATA COLLECTION

A quantitative analysis was conducted using survey methods to examine the relationships between risk communication, perception, and investment decisions. Data were gathered from 465 clients of financial advisers, who were of different demographics in terms of gender, age, education, experience in investment, and annual income. Questionnaires were conducted in a structured manner and were carried out online and as a paper-based survey to obtain the responses of the participants. The process ensured anonymity and confidentiality. The gathered demographic data was analyzed to find the patterns and connections in the financial decision-making. Table 2 represents the distribution of the characteristics of participants in the sample.

TABLE 2
Demographic Profile of Financial Adviser Clients Surveyed

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	280	60.2
	Female	185	39.8
Age (years)	20–30	90	19.4
	31–40	150	32.3
	41–50	130	28.0
	51 and above	95	20.3
Education Level	High School	50	10.8
	Undergraduate	180	38.7
	Graduate	180	38.7
	Postgraduate and above	55	11.8
Investment Experience	Less than 1 year	70	15.1
	1–3 years	150	32.3
	4–6 years	130	28.0
	More than 6 years	115	24.7
Occupation	Private Sector	200	43.0
	Government	120	25.8
	Self-Employed	95	20.4
	Retired/Other	50	10.8

Table 2 presents the demographic information of 465 clients of financial advisors. It shows that, among age categories of 19.4% (20-30), 32.3% (31-40), 28.0% (41-50), and 20.3% (51 and above), 60.2% of the population was male and 39.8% was female. The data on education, experience in investment, and occupation were the highest

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with the biggest proportions (undergraduates at 38.7 %, 1-3 years' experience at 32.3 %, and employees in the private sector at 43.0 %).

3.2 QUESTIONNAIRE

The survey included questions designed to assess participants' emotional responses, investment decision-making processes, and understanding of financial risks using a 5-point Likert scale. Its goal was to obtain the perceptions, cognitions, and behavior of the clients regarding risk-related information. The survey questions that were used to measure responses are indicated in Table 3.

TABLE 3
Participants' Questionnaires

Variable	Questions
RCQ	1. How clearly does your financial adviser explain potential investment risks? 2. What methods does your adviser use to make risk information understandable?
RP	1. How likely do you think your investments could result in significant losses? 2. Why do you feel confident or uncertain about assessing financial risks?
IC	1. How often do you allocate funds across both risky and safe assets? 2. What factors influence your decisions to adjust your investment portfolio?
ERR	1. How anxious do you feel when considering potential investment losses? 2. Why do certain investments make you feel confident or worried?
ISB	1. How often do you seek additional information before investing? 2. What sources do you consult to better understand investment risks?

Risk Perception using Logistic Regression (RPLR)

LR is an efficient and popular classification method that identifies a linear combination of inputs and maps it into a probability ranging from 0 to 1 using a sigmoid function to describe the possibility of a specific outcome. LR is appropriate for problems with binary and multiclass classification, especially when presenting the impact of multiple sustainability indices. Decision-makers can make data-driven choices because of LR's capability to correctly discriminate companies according to their sustainability scores. This approach optimizes feature selection to increase the model's predictive performance, making it ideal for usage in big, highly-dimensional data sets in future power systems.

Sigmoid as a basis constructs linear models that are helpful for classification and also probability estimation. The definition of the sigmoid function in Equation (1).

$$f(y) = \frac{1}{1 + f^{-y}} \tag{1}$$

Where y is the linear combination of features

Conditional Probability Calculation: Equation (2) uses the conditional probability computation below to evaluate sustainability performance.

$$o(Z = 1|w) = \frac{\exp{(x.w + a)}}{1 + \exp{(x.w + a)}} \tag{2}$$

$$o(Z = 0|w) = \frac{1}{1 + \exp\,(x.w + a)}$$

Where high sustainability performance with $Z = 1, Z = 0$: Low performance in terms of sustainability, x: feature vector that depicts social, economic, and environmental indicators. w: Vector of weight, a: The bias term.

Set for Training: The training set of inputs used to assess businesses in Equation (3).

$$C = \{(w_1, z_1), (w_2, z_2), \dots, (w_m, z_m)\} \tag{3}$$

Where the sustainability aspects of the j^{th} firm are represented. the sustainability categorization (0 = Low, 1 = High) is represented. m: number of firms in training. w_j: feature vector for firm j.

Likelihood Function: The likelihood function for $w_j \in Q, w_j \in \{0,1\}$, in Equation (4).

$$\prod_{j=1}^{m} [\psi(w_j)]^{z_j} [1 - \psi(w_j)]^{1-z_j} \tag{4}$$

Log-Likelihood Function: The above-mentioned function has the following logarithmic expression in Equation (5):

$$\begin{aligned} K(x) &= log \left\{ \prod_{j=1}^{m} [\psi(w_j)]^{z_j} [1 - \psi(w_j)]^{1-z_j} \right\}, \\ &= \sum_{j=1}^{M} [z_j log\pi(w_j) + (1 - z_j) \log\,(1 - \pi(w_j))] \end{aligned} \tag{5}$$

Where the chance for successful sustainability performance is represented by $\pi(w_j)$.

Final Model Outcome: The following model is the last one used to assess sustainability performance in Equation (6).

$$\begin{aligned} o(Z = 1|w) = \frac{\exp(\hat{x}.w + a)}{1 + \exp(\hat{x}.w + a)}, \quad o(Z = 0|w) \\ = \frac{1}{1 + \exp(\hat{x}.w + a)} \end{aligned} \tag{6}$$

Where $\hat{z}$ is the optimized feature vector from SSFLA. By examining the environmental, economic, and social performance metrics of firms in new type power systems, this model provides an organized way to evaluate their sustainability performance.

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Adaptive Satin Bowerbird Optimization (ASBO)

The ASBO algorithm is a metaheuristic that finds globally optimal solution to multi-datacenter resource scheduling problems. It is a simple, robust, and efficient population-based method that generates candidate solutions within defined limits, guiding the best chances of optimal resource allocation across data centers.

$$Prob_j = \frac{fit_j}{\sum_{m=1}^{NB} fit_m} \quad (7)$$

$$fit_j = \begin{cases} \frac{1}{1+e(w_j)}, & e(w_j) \geq 0 \\ 1+\left|e(w_j)\right|, & e(w_j) < 0 \end{cases} \quad (8)$$

$Prob_j$ is the probability of selecting the j^{th} solution based on fitness, fit_j is the fitness of the j^{th} solution, and NB is the total number of solutions. NB is the error value for the j^{th} solution.

The ASBO approach uses exclusivity to find optimal solutions, based on satin bowerbirds' behavior. The attractiveness of the bower is determined by decorations, allowing for optimization and effective resource scheduling across cloud systems as follows in Equation (9).

$$w_{jl}^{new} = w_{jl}^{old} + \lambda_l \left(\left(\frac{w_{jl} + w_{elite,l}}{2} \right) - w_{jl}^{old} \right) \quad (9)$$

In the given Eq. (15), w_{jl}^{new} represents the updated weight of the j^{th} solution in the l^{th} dimension, w_{jl}^{old} is the old weight of the j^{th} solution in the l^{th} dimension, w_{jl} is the positive weight component and $w_{elite,l}$ is the elite solution weight in the l^{th} dimension. λ is the step size factor in the l^{th} dimension.

In the mutation process after each round of the ESBO method, the solution w_{jl}^{old} is randomly adjusted according to defined probabilities. This mutation process uses a standard normal M distribution and the new solution w_{jl}^{new} is created based on the mean of the previous solution w_{jl}^{old} and a defined variance σ^2 . The mutation is defined mathematically as in Equation (10).

$$\lambda_l = \frac{\alpha}{1+o_i} \quad (10)$$

$$w_{jl}^{new} \sim M\left(w_{jl}^{old}, \sigma^2\right) \quad (11)$$

$$M\left(w_{jl}^{old}, \sigma^2\right) = w_{jl}^{old} + \left(\sigma^* M(0,1)\right) \quad (12)$$

Where $M\left(w_{jl}^{old}, \sigma^2\right)$ is the normal distribution, in which the values resemble some random variation drawn from a mean of the normal distribution and the variance σ of the normal distribution. It adds diversity to the population and ultimately helps the algorithm effectively explore the solution space so it can schedule resources across the data centers optimally.

4. STATISTICAL ANALYSIS

The approach focuses on how communication shapes perceptions of financial risk and directs investment choices.Using SPSS version 27, descriptive statistics were computed to summarize respondents' characteristics and responses. The correlation analysis and the direct and indirect effects tests were conducted to examine the interrelationship between variables.Regression analysis was used to test the predictive effects, both direct and indirect, of risk communication on risk perception and investment decisions.

4.1 DESCRIPTIVE STATISTICS

It provides a concise summary and a report on the demographic and behavioral patterns of respondents; an attempt is done to formulate a clear picture which correlates communication and perception with financial decision-making. Central tendencies and variation were computed by means of mean, standard deviation (SD) and frequency distributions. This is shown in Equation (13).

$$T = \sqrt{\frac{\sum |w - \bar{w}|^2}{m - 1}} \tag{13}$$

Where T represents SD, it can be considered the variation of the investors (w) around the mean $(\bar{w})$. In this analysis, the consistency of the responses of the study participants on a sample (m) is articulated and the effect of communication on their involvement and financial decision-making.

TABLE 4
Descriptive Statistics of Participants' Responses on Key Measures

Variable	Mean	SD	Minimum	Maximum
RCQ	3.85	0.72	2.10	4.95
RP	3.62	0.81	1.95	4.88
IC	3.78	0.75	2.05	4.92
ERR	3.55	0.69	2.00	4.85
ISB	3.91	0.77	2.20	5.00

Table 4 indicates that the range of mean values is between 3.55 (ERR) and 3.91 (ISB), with moderate to high values obtained in the measure. The standard deviations (0.69-0.81) are used to show the consistency of responses. The range of responses by the participants is represented by minimum and maximum values (1.95-5.00).

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4.2 CORRELATION ANALYSIS

It quantifies the force and direction of the relationship between variables, which can be used to describe the effect of communication on perception and investment decisions. It determines whether there is an increase or decrease in the responses or behavior of the participants related to greater clarity of risk information. Correction analysis is described in Equation (14).

$$r = \frac{\sum(y_j - \bar{y})(x_j - \bar{x})}{\sqrt{\sum(y_j - \bar{y})^2 \sum(x_j - \bar{x})^2}} \tag{14}$$

Where $\bar{x}$and $\bar{y}$are their means, and $r$varies from –1 to +1, $x_j$and y_j are separate scores for two variables, representing positive or negative correlations between variables. The correlation analysis of the variables is shown in Figure 2.

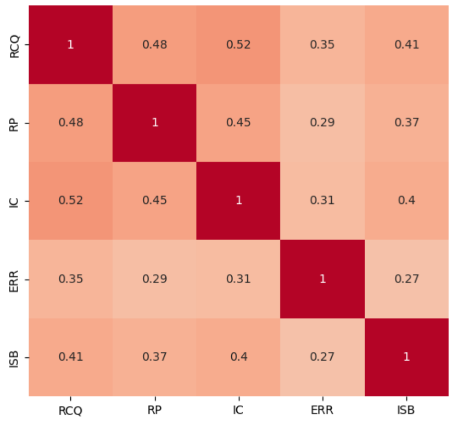

FIGURE 2: Correlation Coefficients Among Participants' Financial Decision-Making Variables

The graph presents positive relationships between all the variables with the range of 0.27 (ERR-ISB) to 0.52 (RCQ-IC), which indicates moderate relationships. RCQ has a long-standing relationship with IC (0.52) and RP (0.48), which indicates that the perception and investment decisions are affected by clear communication.

4.3 REGRESSION ANALYSIS

It considers the predictability or effect of one or more independent variables on a dependent variable, and therefore, it assists one to appreciate the effects of communication on perception and investment choices. It measures the fortitude and the direction of these relationships and tests indirect and direct effects. It is formulated as Equation (15).

$$Y = a + bX \tag{15}$$

Where:

- Y = dependent variable

- X = independent variables
- a = intercept
- b = slope coefficient

This analysis can be used to evaluate how differences in communication and perception affect the financial decisions made by participants.

TABLE 5
Regression Analysis of Factors Influencing Financial Decision-Making Outcomes.

Variable	β	Standard Error	t-Value	p-Value
RCQ	0.420	0.050	8.40	<0.001
RP	0.310	0.060	5.17	<0.001
IC	0.365	0.055	6.64	<0.001
ERR	0.180	0.040	4.50	<0.001
ISB	0.250	0.050	5.00	<0.001

Table 5 reveals the standardized coefficients (b) between 0.180 (ERR) and 0.420 (RCQ), which is the amount of impact of each variable. RCQ affects the results the most, and the next impact is IC (0.365) and RP (0.310), and the lowest impact is produced by ERR (0.180) and ISB (0.250).

4.4 PERFORMANCE ANALYSIS

To evaluate the effectiveness of the proposed model, its predictive performance was compared with baseline models commonly used in financial decision-making and behavioral analysis. These baseline models include:

- Logistic Regression without mediation (BL-LR)
- Multiple Linear Regression (BL-MLR)
- Decision Tree Classifier (BL-DT)
- Support Vector Machine (BL-SVM)

The proposed model incorporates optimized feature interactions and mediation effects, enabling superior predictive capability. Performance was assessed using Accuracy, Precision, Mean Squared Error (MSE), and Mean Absolute Error (MAE). The results demonstrate that the proposed model consistently outperforms baseline approaches, achieving higher classification accuracy and precision while maintaining lower prediction error values (MSE and MAE). This confirms the robustness and reliability of the proposed framework in modeling investor decision behavior under risk.

TABLE 6
Performance Analysis.

Model	Accuracy	Precision	MSE	MAE
Baseline Logistic Regression (BL-LR)	0.81	0.78	0.092	0.241
Baseline Linear Regression (BL-MLR)	0.79	0.76	0.105	0.258
Baseline Decision Tree (BL-DT)	0.83	0.80	0.088	0.232
Baseline Support Vector Machine (BL-SVM)	0.84	0.82	0.081	0.220
RPLR-ASBO	**0.89**	**0.87**	**0.052**	**0.165**

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When compared to all baseline models, the RPLR-ASBO model performs better. It confirms the efficacy of using risk perception and risk communication quality as mediating mechanisms in financial decision modeling by achieving the maximum accuracy and precision while keeping the lowest error values (MSE and MAE).

Figure 3 illustrates the accuracy performance of the baseline models and the RPLR-ASBO Model. The figure shows that the proposed decision framework achieves the highest classification accuracy compared to traditional baseline approaches.

Figure 4 presents a radar plot comparing precision values across baseline models and the RPLR-ASBO Mediated Decision Model. The expanded area covered by the RPLR-ASBO-MDM indicates improved precision in predicting investment decision outcomes.

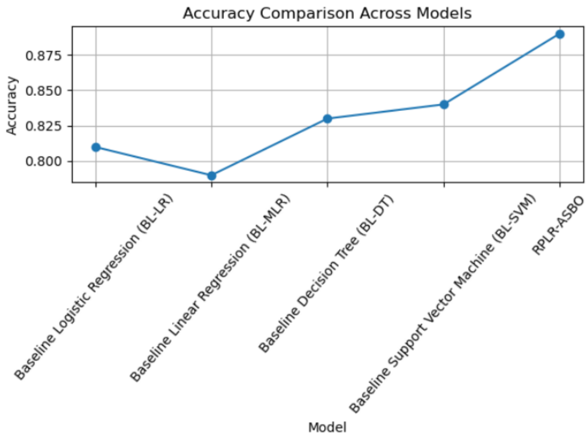

FIGURE 3: Accuracy Comparison

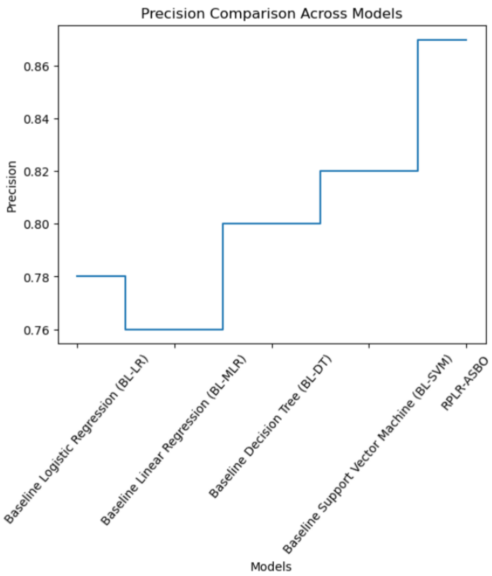

FIGURE 4: Precision Comparison

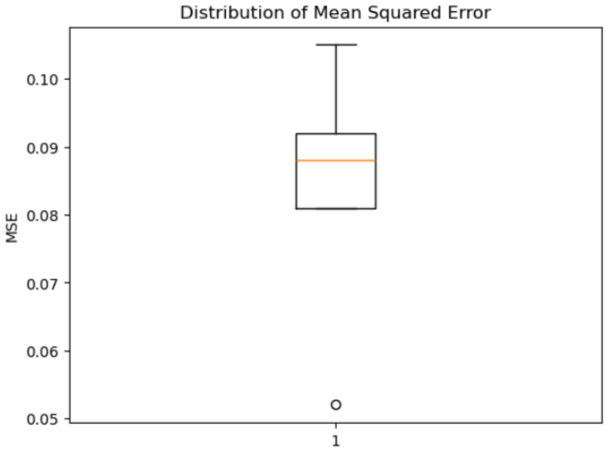

FIGURE 5: MSE Comparison

Figure 5 depicts the distribution of mean squared error (MSE) values across the evaluated models. Lower error dispersion for the RPLR-ASBO Mediated Decision Model indicates higher predictive stability and reduced estimation error.

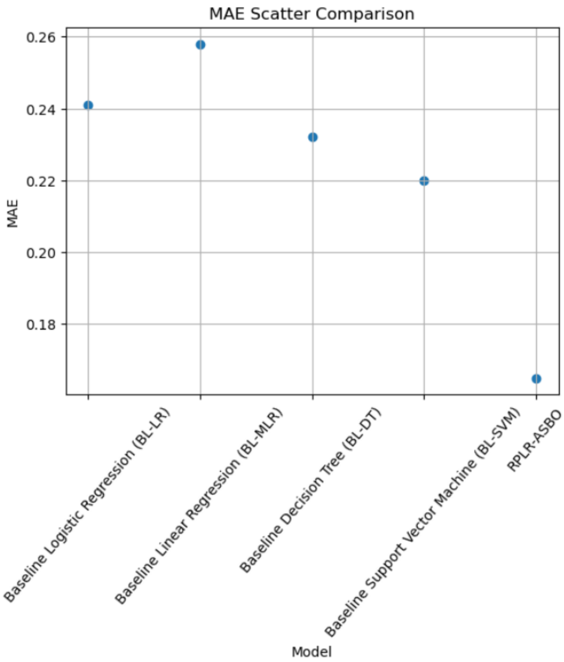

FIGURE 6: MAE Comparison

Figure 6 shows a scatter comparison of mean absolute error (MAE) values for baseline models and the RPLR-ASBO Mediated Decision Model. The reduced MAE value reflects the improved robustness and consistency of the proposed framework.

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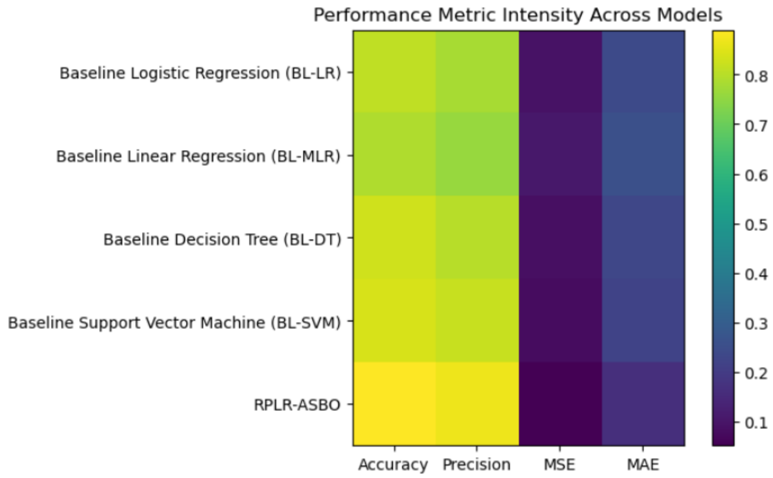

FIGURE 7: Overall Comparison

Figure 7 presents a heatmap-style visualization illustrating the intensity of performance metrics (accuracy, precision, MSE, and MAE) across all evaluated models. The RPLR-ASBO Model exhibits favorable metric intensities, confirming its overall superiority.

5. DISCUSSION

This study, which was backed by empirical data and performance-based evaluation, looked at how investors' perceptions of risk and subsequent financial decisions are influenced by the quality of risk communication. The results show that investors' capacity to understand uncertainty, control their emotions, and make wise investment decisions is greatly improved by effective risk communication. The findings show that perception-driven mechanisms serve as a crucial link between communicated risk information and practical financial actions, which is in line with earlier behavioral finance research.

By quantitatively evaluating the efficacy of the RPLR-ASBO Model against widely known baseline models, the performance analysis reinforces these conclusions. The integrated framework regularly achieves significantly lower error values (MSE and MAE) while outperforming conventional methods in terms of accuracy and precision, as shown in Figures X–V. Instead of depending only on traditional statistical or machine learning models that regard investor decisions as purely rational processes, this performance enhancement emphasizes the benefit of combining behavioral and perceptual factors.

Predictive reliability is improved by incorporating risk perception as a mediating construct, according to the accuracy comparison (Figure 3). Similarly, improved classification consistency is shown by the radar-based precision analysis (Figure 4), indicating that the suggested framework more successfully distinguishes between various investor decision outcomes. Increased model stability and robustness are shown in the MSE and MAE visualizations (Figures 5 and 6), which show a decreased dispersion of error values. The integrated framework ensures balanced performance across all evaluation criteria, as further confirmed by the thorough metric intensity comparison (Figure 7).

Practically speaking, these results highlight the significance of communication tactics that put an emphasis on contextual framing, clarity, and transparency. Financial advisors are more likely to support logical decision-making and reduce behavioral biases when they implement structured communication techniques that are in line with investor perspective. By empirically proving that communication-driven perception is a key predictor of investing behavior rather than just a supporting element, the findings expand on previous research on financial decision-making.

6. CONCLUSION

Using survey data gathered from 465 financial advising clients, this study examined the relationship between risk communication quality, risk perception, and financial decision-making. The research offers a thorough understanding of how transmitted risk information is converted into investment decisions by combining behavioral characteristics with quantitative performance evaluation.

The empirical findings verify that investment decisions are impacted by risk communication quality in both direct and indirect ways, with risk perception acting as a key mediating factor. When compared to baseline models, the RPLR-ASBO Model performs better, attaining greater precision and accuracy while reducing prediction errors. These results confirm that adding behavioral and perceptual aspects to financial decision modeling is beneficial.

The study has limitations despite its contributions, such as its cross-sectional research approach and dependence on self-reported survey data. Causal inference and generalizability across various investor demographics and market conditions may be limited by these considerations. However, by emphasizing the crucial role of communication-driven perception in financial decision-making, the findings provide significant theoretical and practical consequences.

Future studies could build on this work by using cross-cultural samples, longitudinal designs, and sophisticated machine learning approaches to improve predictive power. The applicability of the approach would further be strengthened by combining perceptual metrics with actual investment transaction data. Overall, this study adds to the body of knowledge in behavioral finance by showing that successful risk communication greatly enhances the results of investment decisions when it is methodically combined with risk perception.

7. ADVANTAGES OF THE PROPOSED MODEL

Compared to traditional financial decision-making models, the suggested risk communication–risk perception–investment decision paradigm has a number of advantages. In order to provide a more comprehensive picture of investor behavior, it first combines behavioral and perceptual aspects (risk perception, emotional reaction, and information-seeking behavior) with conventional financial decision variables. Second, the model's external validity is improved by empirical validation utilizing actual investor data (n = 465) as opposed to speculative or experimental scenarios. Third, the approach illustrates how risk communication quality affects investment decisions through risk perception by capturing both direct and indirect (mediated) effects. Lastly, financial advisers can create focused communication strategies to

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enhance investor outcomes since structured statistical modeling guarantees interpretability and practical applicability.

8. LIMITATIONS

This study has certain drawbacks despite its contributions. First, response bias may be present because the study is based on self-reported survey data. Second, the sample may not be as generalizable to institutional or self-directed investors because it only includes financial advisor clients. Third, causal inference over time is limited by the cross-sectional structure of the data. Furthermore, cultural and geographical aspects that could affect risk perception and communication efficacy were not specifically considered.

9. FUTURE WORK

This work can be expanded in a number of ways by future research. It is possible to investigate how risk perception changes over time in response to communication tactics using longitudinal data. Studies that compare cultures could investigate how investor behavior varies depending on the situation. Predictive performance may be further improved by sophisticated machine learning models like deep neural networks and ensemble learning. Lastly, the behavioral-financial relationship would be strengthened and model robustness would be enhanced by combining actual transactional investment data with perceptual metrics.

DECLARATION

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.
Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.
Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.
Competing interests: here are no have no conflicts of interest to declare.
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