The Impact of Investor Sentiment on Portfolio Optimization in the Tehran Stock Exchange and Cryptocurrency Markets

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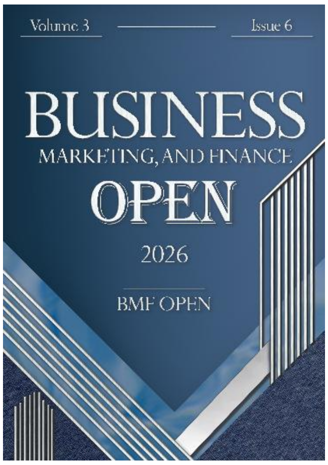

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Abstract: The present study was conducted with the aim of examining the impact of investor sentiment on portfolio optimization in the stock market and cryptocurrency market using the framework of Cumulative Prospect Theory (CPT). In terms of purpose, this research is applied-developmental, and in terms of nature, it is descriptive-analytical, conducted within the framework of the critical realism paradigm and employing a mixed-methods (qualitative–quantitative) approach. In the qualitative section, interviews were conducted with 12 financial experts to localize behavioral dimensions. In the quantitative section, behavioral data were collected through a questionnaire from 320 active investors and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Financial data consisted of daily time series of 10 selected assets (5 stocks from the Tehran Stock Exchange and 5 cryptocurrencies) over the period 2020–2025, which were modeled using GARCH model with Student's t and GED distributions, as well as Student-t copula functions. Portfolio optimization was performed using the CPT approach and Monte Carlo simulation. The results indicated that investor sentiment (including loss aversion with a factor loading of 0.703, herding behavior with a factor loading of 0.731, and fear of missing out (FOMO) with a factor loading of 0.621) has a negative and significant effect on portfolio optimization. Path coefficients were significant for the mixed portfolio (−0.702, t = 20.104), stock portfolio (−0.671, t = 16.552), and cryptocurrency portfolio (−0.670, t = 18.002). The intensity of loss aversion in the cryptocurrency market ($\lambda = 2.31$) was higher than in the stock market ($\lambda = 2.10$). The GARCH models confirmed high volatility persistence ($\alpha + \beta$ close to 0.98) and heavy-tailed distributions in both markets. The Student-t copula indicated strong tail dependence within the crypto market ($\rho = 0.68$) and low correlation between the two markets. CPT-based optimization generated higher subjective value compared to the mean–variance approach (0.091 versus 0.068), but resulted in more conservative portfolios. Investor sentiment—particularly loss aversion and herding behavior—has a strong negative impact on portfolio optimization in both stock and cryptocurrency markets, and this effect is intensified in multi-market and highly volatile environments. The CPT model, through asymmetric modeling of gains and losses, demonstrates a strong capability in explaining actual investor behavior.

Keywords: Investor sentiment, Cumulative Prospect Theory, Portfolio optimization, GARCH model, Copula functions, Tehran Stock Exchange, Cryptocurrencies

1. Introduction

Financial markets have traditionally been analyzed under the assumption of rational decision-making, where investors are presumed to maximize expected utility based on available information. Classical frameworks such as

Modern Portfolio Theory (MPT) emphasize the trade-off between risk and return and provide mathematical tools for optimal asset allocation [1]. However, empirical evidence accumulated over recent decades has consistently challenged the assumption of full rationality, demonstrating that investor behavior is often influenced by psychological, emotional, and cognitive factors that deviate from normative models [2, 3]. These deviations have led to the emergence and rapid development of behavioral finance, which integrates insights from psychology into financial decision-making and provides a more realistic explanation of market anomalies and investor behavior [4].

One of the central constructs in behavioral finance is investor sentiment, which refers to the overall attitude, mood, or psychological bias of investors toward market conditions and investment opportunities. Investor sentiment has been shown to significantly influence asset pricing, return dynamics, and market efficiency [5, 6]. In emerging and less efficient markets, such as the Tehran Stock Exchange, the impact of sentiment-driven trading is particularly pronounced due to information asymmetry and limited institutional oversight [7, 8]. Studies indicate that heightened sentiment can lead to synchronized movements in stock returns and distortions in price discovery processes, ultimately affecting portfolio performance and optimization outcomes [9].

The growing complexity of financial markets has further intensified the importance of understanding investor sentiment, particularly with the emergence of digital assets and cryptocurrencies. Since the introduction of Bitcoin as a decentralized digital currency [10], the cryptocurrency market has evolved into a highly volatile and sentiment-driven environment. Unlike traditional financial markets, cryptocurrencies are heavily influenced by speculative behavior, social media narratives, and external shocks, which amplify emotional responses among investors [11, 12]. Empirical research has demonstrated that even non-fundamental factors such as public statements, online discussions, and social media activity can significantly impact cryptocurrency prices and volatility [13].

In this context, investor sentiment plays a critical role in shaping market dynamics across both traditional and digital asset classes. Research shows that sentiment-driven behaviors such as herding, fear of missing out (FOMO), and overreaction are particularly prevalent in cryptocurrency markets due to their decentralized structure and lack of intrinsic valuation benchmarks [14, 15]. Furthermore, sentiment spillover effects between stock markets and cryptocurrencies have been observed, indicating interconnected behavioral patterns across financial systems [16]. These findings suggest that a comprehensive analysis of portfolio optimization must account for behavioral factors across multiple markets rather than focusing solely on traditional financial assets.

Recent advancements in portfolio optimization methodologies have sought to incorporate behavioral considerations into mathematical models. While traditional optimization approaches, such as mean–variance optimization, rely on assumptions of normal return distributions and rational preferences, newer frameworks attempt to integrate psychological biases and nonlinear preferences into the decision-making process [17, 18]. In particular, models based on behavioral theories, such as prospect theory and its extensions, provide a more accurate representation of how investors perceive gains, losses, and probabilities [19]. These models recognize that investors exhibit loss aversion, nonlinear probability weighting, and reference-dependent preferences, all of which significantly influence portfolio allocation decisions.

The integration of behavioral finance into portfolio optimization is particularly relevant in environments characterized by high volatility and uncertainty. Cryptocurrency markets, for example, exhibit extreme price fluctuations, heavy-tailed return distributions, and strong tail dependence, which cannot be adequately captured by traditional models [20, 21]. In such contexts, behavioral biases become more pronounced, leading to suboptimal investment decisions and increased exposure to risk [22, 23]. Consequently, incorporating investor sentiment into optimization models can enhance their explanatory power and improve their practical applicability in real-world financial decision-making.

In parallel, methodological advancements in data analysis and computational techniques have enabled more sophisticated modeling of investor behavior and market dynamics. The use of machine learning, sentiment analysis, and natural language processing has facilitated the extraction of behavioral signals from large-scale data sources, including social media and news platforms [24]. These approaches allow researchers to quantify investor sentiment more accurately and integrate it into financial models, thereby bridging the gap between theoretical constructs and empirical observations [25]. Moreover, hybrid models that combine traditional econometric techniques with behavioral insights have demonstrated improved performance in predicting market movements and optimizing portfolios [19].

Despite these advancements, there remains a significant research gap in the simultaneous examination of investor sentiment across multiple markets and its impact on portfolio optimization. While numerous studies have investigated sentiment effects in either stock markets or cryptocurrency markets individually, limited attention has been given to their combined analysis within a unified framework [26, 27]. This gap is particularly relevant in the context of diversified investment strategies, where investors allocate resources across both traditional and digital assets. Understanding how sentiment influences portfolio allocation decisions in such multi-market environments is essential for developing robust and adaptive investment strategies.

Furthermore, empirical studies highlight that investor sentiment does not only affect return levels but also alters risk perceptions and portfolio efficiency. Behavioral biases can lead to under-diversification, excessive risk-taking, or overly conservative investment strategies, depending on market conditions and investor characteristics [28]. These effects are magnified in periods of market stress or uncertainty, where emotional responses dominate rational decision-making processes [29]. Therefore, incorporating sentiment into portfolio optimization models is not merely an academic exercise but a practical necessity for improving investment outcomes.

In the context of the Tehran Stock Exchange, behavioral factors play a particularly important role due to the unique structural characteristics of the market, including high participation of individual investors and limited availability of advanced financial instruments. Studies have shown that sentiment-driven trading behavior significantly influences market dynamics in Iran, leading to deviations from fundamental values and increased volatility [9]. At the same time, the rapid growth of cryptocurrency adoption among Iranian investors has introduced new dimensions of risk and behavioral complexity, further emphasizing the need for integrated analytical frameworks [30].

Moreover, the interaction between investor sentiment and portfolio optimization is not uniform across different asset classes. Evidence suggests that the impact of sentiment is stronger in markets characterized by higher uncertainty and lower informational efficiency, such as cryptocurrencies, compared to more established stock markets [4, 14]. This heterogeneity underscores the importance of comparative analyses that examine the differential effects of sentiment across markets and asset types. Such analyses can provide valuable insights into how investors adjust their behavior in response to varying levels of risk and uncertainty.

In addition, recent studies have emphasized the role of behavioral biases in shaping investment strategies and portfolio outcomes. Biases such as loss aversion, overconfidence, and herding behavior have been shown to systematically influence asset allocation decisions and portfolio performance [3, 15]. These biases often lead to deviations from optimal investment strategies, resulting in lower returns or higher risk exposure. By explicitly modeling these behavioral tendencies, researchers can develop more accurate and robust optimization frameworks that reflect real-world investor behavior.

Taken together, the existing literature highlights the critical importance of integrating behavioral factors into portfolio optimization models, particularly in the context of multi-market investment environments. While traditional models provide valuable theoretical foundations, they fail to capture the complexity of human behavior and its impact on financial decision-making. Behavioral approaches, on the other hand, offer a more comprehensive and realistic perspective, enabling better alignment between theoretical models and empirical observations [19].

Therefore, given the increasing relevance of investor sentiment in both traditional and digital financial markets, as well as the limitations of classical optimization models, the present study aims to examine the impact of investor sentiment on portfolio optimization in the Tehran Stock Exchange and cryptocurrency markets within a unified behavioral finance framework.

2. Methodology

The present study is classified, in terms of its objective, as applied–developmental research. Its applied aspect lies in the fact that its findings can be directly utilized in investor decision-making processes, asset allocation strategy design, and risk management within financial markets. In this study, a mixed-methods research design of an explanatory type with a predominance of the quantitative approach is employed. The statistical population in both the qualitative and quantitative sections was defined as follows:

Population and Sample

a) Qualitative Phase (Expert Interviews):

In this phase, the statistical population consisted of experts familiar with behavioral finance, the Iranian capital market, and cryptocurrency markets. The aim was not generalization, but rather the deepening of the theoretical framework, identification of key behavioral dimensions in domestic markets, and validation of indicators based on Cumulative Prospect Theory for the precise design of the quantitative instrument. Sampling was conducted purposively based on a minimum of five years of relevant professional or academic experience and continued until theoretical saturation was achieved.

b) Quantitative Phase (Survey and Financial Data):

At the behavioral level, the statistical population consisted of active investors in the Tehran Stock Exchange and cryptocurrency markets, with the unit of analysis defined as the individual investor. Stratified random sampling was employed, and the sample size was determined as 384 individuals using Cochran's formula; ultimately, 320 valid questionnaires were collected from 450 distributed questionnaires.

At the financial level, the statistical population included all assets in both markets, with asset returns as the unit of analysis. Asset selection was conducted judgmentally based on maximum liquidity and the availability of reliable historical data.

Data Collection Instruments

Data collection in this study was conducted using a combined approach in two sections: library-based and field-based, in order to both establish the theoretical framework and empirically test the hypotheses. In the library section, a systematic review of scientific sources was conducted to identify the foundations of behavioral finance, relevant theories, portfolio optimization models, and appropriate statistical approaches, forming the basis for variable selection, dimensions of investor sentiment, and model formulation.

In the field section, standardized questionnaires grounded in behavioral finance literature and Cumulative Prospect Theory were used to measure investor sentiment as a latent construct, covering dimensions of loss aversion, regret aversion, and mental accounting. The instrument was designed using a Likert scale and, after evaluation and refinement based on expert opinions, was implemented to enhance content validity.

The data collection process was conducted in a logical sequence such that the output of the qualitative phase served as the input for the quantitative phase:

First stage – Library studies: theoretical foundations and initial models were extracted.

Second stage – Qualitative data collection (interviews): semi-structured interviews were conducted with 12 financial experts (including university professors, stock market analysts, and professional cryptocurrency traders). Interview questions were designed based on identified gaps in the CPT literature.

Output of the qualitative phase (input for the quantitative phase): after transcription and content analysis of the interviews, the findings led to the following outcomes:

Confirmation and localization of dimensions: the main dimensions of investor sentiment (loss aversion, regret aversion, and mental accounting) were confirmed and enriched with localized examples relevant to the Iranian market.

Questionnaire design and validation: questionnaire items were developed based on a combination of standard CPT literature and concepts extracted from interviews. Content validity was confirmed by the same experts (and several additional specialists).

Third stage – Quantitative data collection (survey and financial data):

Behavioral survey: the finalized questionnaire was distributed among a sample of 320 investors. The aim was to quantify behavioral parameters (e.g., the intensity of loss aversion) within a large sample and ensure generalizability.

Financial data: simultaneously, price data for selected assets were collected over the specified time period.

Fourth stage – Integration: behavioral parameters estimated from the questionnaire (e.g., mean loss aversion coefficients) were incorporated as inputs into the CPT optimization model, while financial data were used to compute returns and risk within the model.

To ensure data quality, the validity and reliability of research instruments were assessed. Content validity was confirmed through expert evaluation, and reliability was measured using Cronbach's alpha. Acceptable values of these indices indicated internal consistency and reliability of the measurement instruments.

Variable Definition and Operationalization

In this study, investor sentiment was considered the main independent variable and a latent construct, operationalized based on behavioral finance literature and CPT through three dimensions: loss aversion, regret aversion, and mental accounting.

The dependent variable was the performance of the portfolio optimization process, defined not as a behavioral construct but as objective indicators derived from the implementation of mathematical optimization models on financial data and directly used as model outputs.

To capture multidimensional performance, three distinct indicators were employed:

Expected portfolio return, calculated as the weighted average of expected returns of assets in the optimal portfolio (a continuous numerical variable).

Portfolio risk, measured as the standard deviation of simulated portfolio returns (a continuous numerical variable).

Portfolio efficiency, defined as the return-to-risk ratio (e.g., Sharpe ratio or its adjusted versions).

In the questionnaire data analysis (PLS-SEM), these three indicators were treated as observable dependent variables. For each respondent (or cluster of respondents with similar sentiment levels), a separate optimal portfolio was constructed based on their behavioral parameters, and the numerical values of return, risk, and efficiency were extracted and assigned as values of these variables. Therefore, these variables appeared as single-item dependent variables in the PLS-SEM model, making reliability assessment neither feasible nor meaningful.

Theoretical Framework: Cumulative Prospect Theory

The theoretical framework of this study is based on Cumulative Prospect Theory, which rejects the assumption of full rationality and posits that investors evaluate outcomes relative to a reference point rather than final wealth. In this theory, responses to gains and losses are asymmetric, with losses carrying greater psychological weight than equivalent gains. Furthermore, individuals distort probabilities, overestimating small probabilities and underestimating large ones. These characteristics cause investor behavior, especially in volatile markets, to deviate from classical model predictions; thus, CPT enables a more realistic modeling of investor behavior and its impact on portfolio optimization.

Mathematical Formulation of Investor Preferences

Within the CPT framework, investor preferences are modeled through a value function and probability weighting functions. The value function reflects the subjective evaluation of gains and losses and is defined asymmetrically and nonlinearly relative to a reference point:

$$v(x) = \begin{cases} x^{\alpha}, & x \geq 0 \\ -\lambda(-x)^{\beta}, & x < 0 \end{cases}$$

where x denotes the deviation of returns from the reference point, α and β (typically between 0 and 1) represent risk aversion in gains and risk-seeking in losses, respectively, and λ measures loss aversion intensity, with $\lambda > 1$ indicating stronger psychological impact of losses relative to gains.

In addition to the value function, CPT employs probability weighting functions to model distorted probability perceptions. If p represents the objective probability of an outcome, the corresponding subjective probability is obtained through w(p). A commonly used function is the Prelec weighting function:

$$w(p) = \exp(-\delta(-\ln p)^{\gamma})$$

where δ represents the investor's optimism or pessimism toward probabilities, and γ reflects the nonlinearity of the weighting function, enabling representation of overweighting of small probabilities and underweighting of large probabilities.

Mathematical Formulation of CPT-Based Portfolio Optimization

In this study, the portfolio optimization problem is defined as the maximization of cumulative prospect value. Suppose an investor faces N financial assets, and the portfolio weight vector is defined as $w = (w_1, \ldots, w_N)$. Portfolio return is expressed as a linear combination of asset returns:

$$R_p = \sum_{i=1}^{N} w_i R_i$$

The cumulative prospect value of the portfolio, considering the probability distribution of returns and subjective weighting, is defined as:

$$V(R_p) = \sum_{x \geq 0} v(x)\Delta w^{+}(x) + \sum_{x < 0} v(x)\Delta w^{-}(x)$$

where $\Delta w^{+}(x)$ and $\Delta w^{-}(x)$ represent cumulative weights for positive and negative outcomes. The optimization problem is formulated as:

$$\max_w V(R_p)$$

subject to full investment and no short-selling constraints:

$$\sum_{i=1}^{N} w_i = 1, \quad w_i \geq 0$$

This formulation constitutes the core analytical framework of the study and enables examination of the direct impact of investor sentiment on optimal portfolio composition.

Modeling Return Volatility (GARCH)

Financial asset returns typically exhibit conditional heteroskedasticity and volatility clustering. To account for these features, GARCH model family models were employed. The basic GARCH(1,1) model for asset i is defined as:

$$R_{i,t} = \mu_i + \varepsilon_{i,t}$$

$$\varepsilon_{i,t} = \sigma_{i,t} z_{i,t}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2$$

where σ^2 represents conditional variance, and α and β indicate the sensitivity of volatility to past shocks and persistence, respectively. This model enables extraction of standardized residuals required for dependence modeling.

Modeling Dependence Structure Using Copula

After estimating marginal GARCH models, dependence among asset returns was modeled using the Copula approach. Based on Sklar's theorem, the joint cumulative distribution is expressed as:

$$F(R_1, \ldots, R_N) = C(F_1(R_1), \ldots, F_N(R_N))$$

In this study, the Student-t Copula was employed due to its ability to capture tail dependence and extreme co-movements, which is particularly relevant in highly volatile cryptocurrency markets.

Simulation of Portfolio Return Distribution

Following estimation of the joint distribution, Monte Carlo simulation was conducted to generate portfolio return scenarios. In each simulation iteration:

$$R_p^{(k)} = \sum_{i=1}^{N} w_i R_i^{(k)}$$

These scenarios formed the basis for calculating cumulative prospect value and evaluating portfolio performance under various market conditions.

Data Analysis Method

Given the mixed-method nature of the study, data analysis was conducted in two distinct sections using specialized software.

Qualitative data analysis (interviews): interview data were analyzed using thematic analysis with MAXQDA software. Audio files were transcribed, repeatedly reviewed, and open codes were extracted. These codes were then categorized into subthemes and main themes (dimensions of investor sentiment). The results were used for localization and questionnaire refinement.

Quantitative data analysis (survey and financial data):

a) Questionnaire data (behavioral section) were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. Given the exploratory nature of some relationships and non-normality of data (assessed via the Kolmogorov–Smirnov test), this method was appropriate. Reliability was assessed using Cronbach's alpha and composite reliability ($CR > 0.7$). Convergent validity was evaluated via average variance extracted ($AVE > 0.5$), and discriminant validity was confirmed using the Fornell–Larcker criterion and cross-loadings. Structural model evaluation involved path coefficients (β) and t-values via bootstrapping, with

$t > 1.96$ indicating significance at the 95% confidence level. Predictive relevance (Q^2) and explanatory power (R^2) were also reported.

b) Financial data analysis:

Daily returns were calculated using logarithmic returns:

$R_{i,t} = \ln(P_{i,t} / P_{i,t-1})$

Variance as a risk measure was computed as:

$\sigma_i^2 = (1 / (T-1)) \sum_{t=1}^{T} (R_{i,t} - \bar{R}_i)^2$

Volatility modeling was performed using GARCH(1,1). Nonlinear dependence was modeled via the Student-t Copula:

$F(R_1, \ldots, R_N) = C_\theta(F_1(R_1), \ldots, F_N(R_N))$

Monte Carlo simulation was applied to generate portfolio return scenarios:

$R_p^{(k)} = \sum_{i=1}^{N} w_i R_i^{(k)}$

Finally, CPT-based portfolio optimization was conducted using the objective function:

$\max_w V(R_p) = \sum_{(x \geq 0)} v(x)\Delta w^+(x) + \sum_{(x < 0)} v(x)\Delta w^-(x)$

subject to:

$\sum_{i=1}^{N} w_i = 1, \quad w_i \geq 0$

3. Findings and Results

This section was developed to test the research hypotheses and answer the main research question, namely, to examine the impact of investor sentiment on the portfolio optimization process in the two markets of the Tehran Stock Exchange and cryptocurrencies.

Modeling the Dependence Structure among Assets Using Copula

After estimating the marginal GARCH(1,1) models and extracting the standardized residuals, the nonlinear dependence structure, and particularly tail dependence, among asset returns was modeled using the Copula approach. Based on Sklar's theorem, the joint cumulative distribution of returns is expressed as $F(R_1, \ldots, R_N) = C(F_1(R_1), \ldots, F_N(R_N))$, where $F_i$denotes the marginal distribution of each asset {obtained from GARCH} and Cdenotes the Copula function.

In this study, several Copula families, including Gaussian, Student-t, Clayton, Gumbel, Frank, and their rotated versions, were fitted. Final model selection was based on the Akaike information criterion (AIC), Bayesian information criterion (BIC), goodness-of-fit tests {such as Cramér–von Mises}, and the model's ability to capture tail dependence. The results clearly showed that the Student-t Copula provided the best fit, which is consistent with the recent finance literature, particularly in highly volatile markets such as cryptocurrencies. The Student-t Copula is capable of modeling symmetric tail dependence {equal upper and lower tail dependence} and severe joint shocks, whereas the Gaussian Copula has zero tail dependence, and Archimedean Copulas {such as Clayton and Gumbel} better describe asymmetric dependence; however, in the empirical data of the present study, the Student-t Copula was superior.

Monte Carlo Simulation for Generating the Portfolio Return Distribution

After estimating the marginal GARCH(1,1) models and the joint dependence model based on the Student-t Copula, the next stage was the generation of realistic portfolio return scenarios using the Monte Carlo simulation method. This method makes it possible to evaluate the full distribution of portfolio returns under actual market uncertainty and provides the basis for calculating cumulative prospect value and CPT-based portfolio optimization.

The simulated distribution successfully reproduced actual market characteristics: negative skewness {losses greater than gains} and substantially higher kurtosis in the portfolio containing cryptocurrencies. Conditional risk {CVaR} in the crypto portfolio was nearly three times that of the Tehran stock portfolio. The combined portfolio demonstrated the benefits of diversification through a substantial reduction in risk {from 3.89% to 2.21%}, although it still exhibited high kurtosis, which stemmed from the Copula tail dependence.

Table 1. Comparison of simulated risk indicators under different dependence models

Dependence Model	Total Portfolio Standard Deviation (%)	VaR 95% (%)	CVaR 95% (%)	Distribution Kurtosis
Student-t Copula (selected)	2.35	-3.95	-6.58	9.12
Gaussian Copula	2.18	-3.62	-5.41	4.87
Full Independence (without Copula)	1.95	-3.27	-4.89	3.92

The use of the Gaussian Copula or the assumption of independence significantly underestimates tail risk (CVaR is approximately 18%–25% lower). This result demonstrates the importance of correctly modeling tail dependence in highly volatile markets; ignoring it leads to portfolios that appear low-risk but are in fact vulnerable under crisis conditions.

Table 2. Monte Carlo simulation convergence (mean and standard deviation of total portfolio returns)

Number of Simulation Iterations	Mean Return (%)	Standard Error of Mean Estimate	Standard Deviation of Returns (%)	Standard Error of σ Estimate
1,000	0.161	0.023	2.38	0.052
5,000	0.160	0.010	2.36	0.023
10,000	0.160	0.007	2.35	0.016
20,000	0.160	0.005	2.35	0.011

Rapid convergence was observed after 10,000 iterations. The standard error of the mean was less than 0.01%, and for the standard deviation it was less than 0.7%, confirming the high precision of the simulation.

Table 3. Effect of CPT parameters on simulated prospect value (equal-weighted portfolio)

CPT Parameter Scenario	α = β	λ	CPT Value of Stock Portfolio	CPT Value of Crypto Portfolio	CPT Value of Combined Portfolio
Rational investor (MV)	1.00	1.00	0.078	0.241	0.160
Sample mean (from questionnaire)	0.88	2.10	0.031	0.068	0.052
High loss aversion (crypto)	0.85	2.30	0.026	0.049	0.041
Low loss aversion (stocks)	0.91	1.90	0.042	0.092	0.071

The CPT value was substantially lower than the expected return under the mean–variance framework, indicating the effect of loss aversion. In the portfolio containing cryptocurrencies, the decline in CPT value was greater (due to thicker tails and more severe losses in the simulated scenarios). This finding constitutes the main basis for hypothesis testing: higher investor sentiment leads to lower subjective portfolio value, especially in a highly volatile market. Monte Carlo simulation successfully reproduced the actual statistical characteristics of the market (heteroskedasticity, tail dependence, skewness, and kurtosis) and generated the portfolio return distribution with high precision. This distribution served as the main input for the final stage of portfolio optimization based on cumulative prospect theory, which is presented in the following section.

Portfolio Optimization Based on Cumulative Prospect Theory (CPT)

In the final stage of the financial analysis, the portfolio optimization problem was solved using the framework of cumulative prospect theory (CPT). Unlike the Markowitz mean–variance model, which assumes full rationality, this approach directly incorporates investors' behavioral preferences (loss aversion, probability distortion, and evaluation relative to a reference point) into the objective function.

Formulation of the Optimization Problem:

The prospect value of the portfolio was calculated as follows:

$$V(R_p) = \sum_{x \geq 0} v(x) \cdot \Delta w^+(x) + \sum_{x<0} v(x) \cdot \Delta w^-(x)$$

where:

$$v(x) = \begin{cases} x^\alpha & x \geq 0 \\ -\lambda(-x)^\beta & x < 0 \end{cases}$$

$w^+$and $w^-$are the cumulative probability weighting functions for gains and losses, respectively (based on the Prelec formula).

The CPT parameters $\alpha, \beta, \lambda, \delta, \gamma$were estimated from the behavioral data [31], and the sample mean was used as the model input.

Optimization Problem:

$$\max_w V(R_p)$$

subject to:

$$\sum_{i=1}^{N} w_i = 1$$

$w_i \geq 0$(no short selling)

Reference point = 0 (zero return)

The optimization algorithm was a genetic algorithm (GA) with 500 generations and a population size of 200, due to the nonlinear and discontinuous nature of the CPT value function.

The number of input scenarios was 10,000 scenarios generated from the Monte Carlo simulation (Copula-GARCH).

Three optimization scenarios were implemented:

A portfolio invested only in the Tehran Stock Exchange (5 stocks).

A portfolio invested only in the cryptocurrency market (5 cryptocurrencies).

A combined portfolio (10 assets).

Table 4. Estimated CPT parameters from behavioral data

Parameter	Description	Total Sample Value	Value in Tehran Stock Investors	Value in Cryptocurrency Investors	Difference (p-value)
α	Diminishing sensitivity in gains	0.88	0.91	0.85	< 0.01
β	Diminishing sensitivity in losses	0.88	0.90	0.86	< 0.05
λ	Loss aversion coefficient	2.10	1.92	2.31	< 0.001
δ	Probability weighting parameter (optimism/pessimism)	0.74	0.78	0.69	< 0.01
γ	Nonlinearity of weighting function	0.68	0.71	0.64	< 0.05

Loss aversion (λ) is significantly higher among cryptocurrency market investors (2.31 versus 1.92), which is consistent with the higher volatility of this market and the experience of more severe losses. Lower values of α and β in the crypto market indicate stronger diminishing sensitivity (greater risk-seeking behavior in the loss domain).

Table 5. Optimal portfolio weights under different approaches

Asset	Weight in MV (Mean–Variance)	Weight in CPT (Total Sample)	Weight in CPT (Stocks Only)	Weight in CPT (Crypto Only)	Weight in CPT (Combined)
Mobarakeh Steel	0.22	0.28	0.35	–	0.30

National Copper	0.20	0.25	0.30	–	0.27
Persian Gulf Petrochemical	0.25	0.27	0.20	–	0.24
Mellat Bank	0.18	0.12	0.10	–	0.09
Iran Khodro	0.15	0.08	0.05	–	0.06
Bitcoin	0.30	0.18	–	0.32	0.16
Ethereum	0.28	0.15	–	0.28	0.13
Binance Coin	0.20	0.12	–	0.22	0.10
Ripple	0.12	0.06	–	0.10	0.05
Cardano	0.10	0.04	–	0.08	0.03

Under the CPT approach, the weights of high-risk assets (such as Iran Khodro and cryptocurrencies other than Bitcoin and Ethereum) decrease significantly. Due to loss aversion, the behavioral investor avoids assets with a high probability of severe losses, even if they offer high expected returns.

Table 6. Comparison of optimal portfolio performance (based on 10,000 scenarios)

Performance Metric	MV Total	CPT Total	MV Stocks	CPT Stocks	MV Crypto	CPT Crypto
Expected Return (%)	0.187	0.142	0.081	0.074	0.291	0.198
Standard Deviation (%)	2.12	1.78	1.45	1.32	4.02	3.41
Sharpe Ratio (risk-free = 0)	0.088	0.080	0.056	0.056	0.072	0.058
CPT Value	0.068	0.091	0.042	0.058	0.031	0.074
VaR 95% (%)	-3.68	-2.91	-2.41	-2.12	-7.45	-5.82
CVaR 95% (%)	-5.92	-4.68	-3.78	-3.29	-12.31	-9.47

The CPT portfolio exhibits higher subjective value (V = 0.091 versus 0.068), although its expected return and Sharpe ratio are lower. This finding clearly reflects the impact of investor sentiment: the behavioral investor is willing to sacrifice part of the return to avoid severe losses (approximately 20% reduction in CVaR). The difference is more pronounced in the cryptocurrency market: the CPT value of the optimal portfolio is more than double that of the MV portfolio (0.074 versus 0.031), confirming that investor sentiment has a stronger effect in highly volatile markets.

Table 7. Difference in CPT value between optimal and equal-weighted portfolios

Portfolio Type	CPT Value (Equal-Weighted)	CPT Value (Optimal)	Increase in CPT Value (%)
Tehran Stock Exchange	0.042	0.058	38.1%
Cryptocurrencies	0.031	0.074	138.7%
Combined	0.052	0.091	75.0%

CPT-based optimization produces the greatest improvement in the cryptocurrency market (138.7% increase), which directly supports Hypothesis 3 of the study (stronger effect of investor sentiment in the cryptocurrency market). The findings of this section indicate that incorporating investor sentiment into the optimization process shifts portfolio composition toward more stable assets and significantly increases the investor's subjective value. This effect is substantially stronger in the cryptocurrency market due to higher volatility and stronger loss aversion among investors.

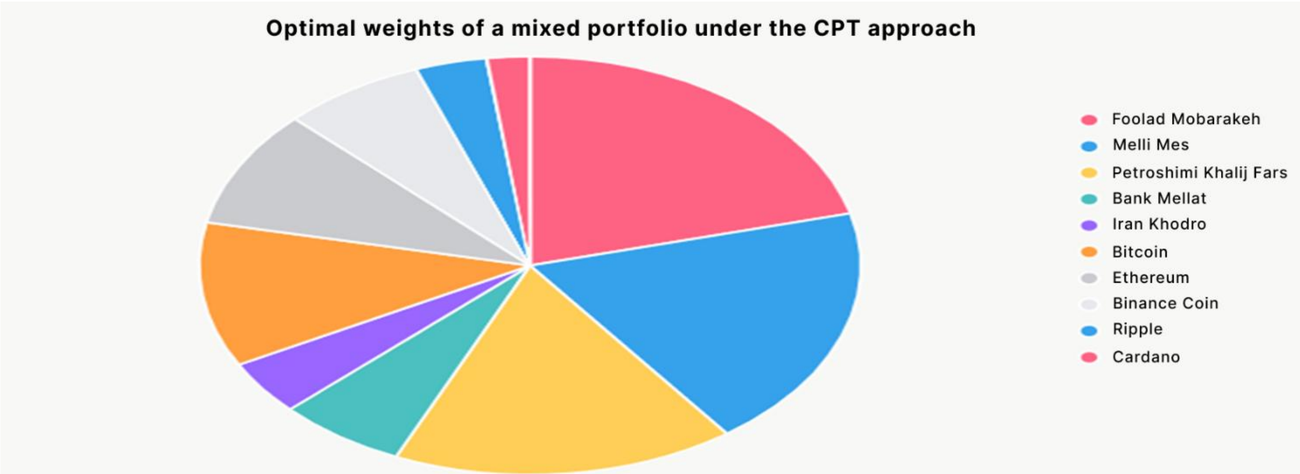

Figure 1: Optimal weights of the combined portfolio under the CPT approach

This pie chart illustrates the distribution of optimal weights under CPT. More than 90% of the weight is allocated to Tehran Stock Exchange equities (particularly the three large stocks: steel, copper, and petrochemical), while cryptocurrencies account for only about 47% of the weight (with concentration on Bitcoin and Ethereum). This conservative allocation reflects investor loss aversion, leading to avoidance of highly volatile assets.

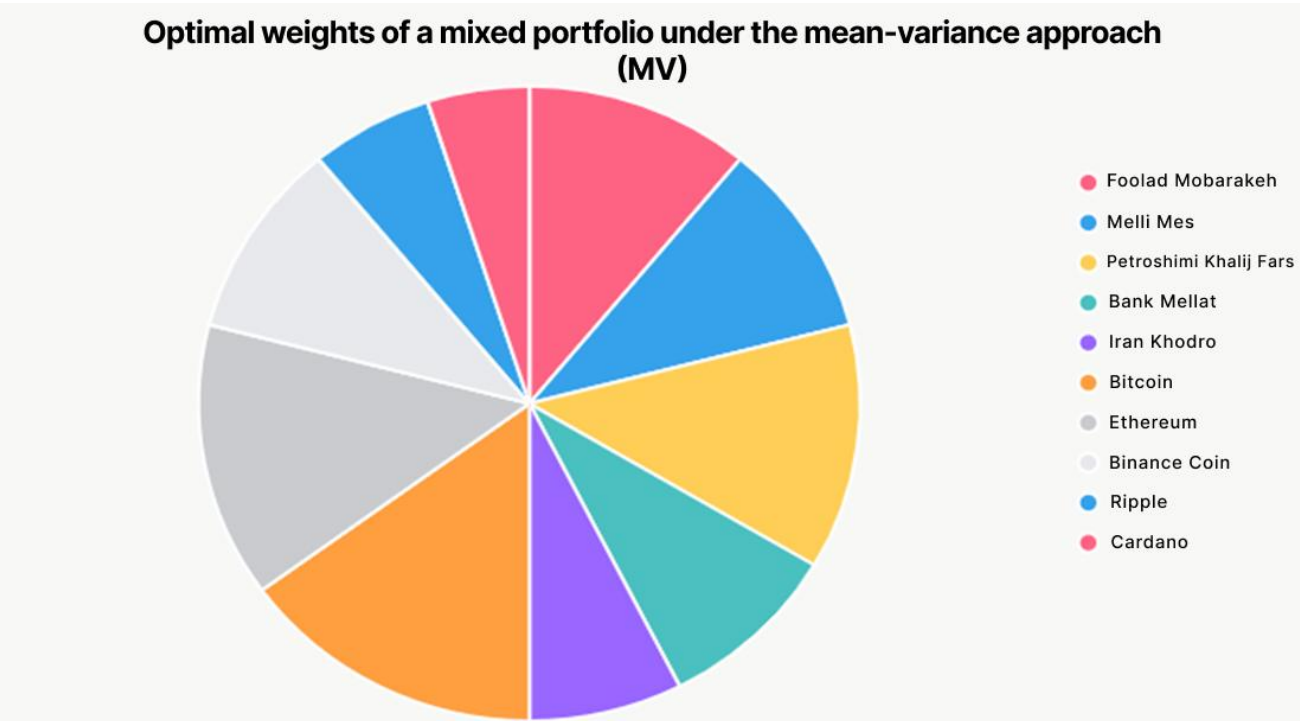

Figure 2: Combined portfolio weights under the mean–variance (MV) approach

Under the classical mean–variance approach, a larger share is allocated to cryptocurrencies (approximately 60%), as this approach focuses solely on expected return and variance and does not incorporate subjective loss aversion. This visual comparison highlights the fundamental difference between rational and behavioral models.

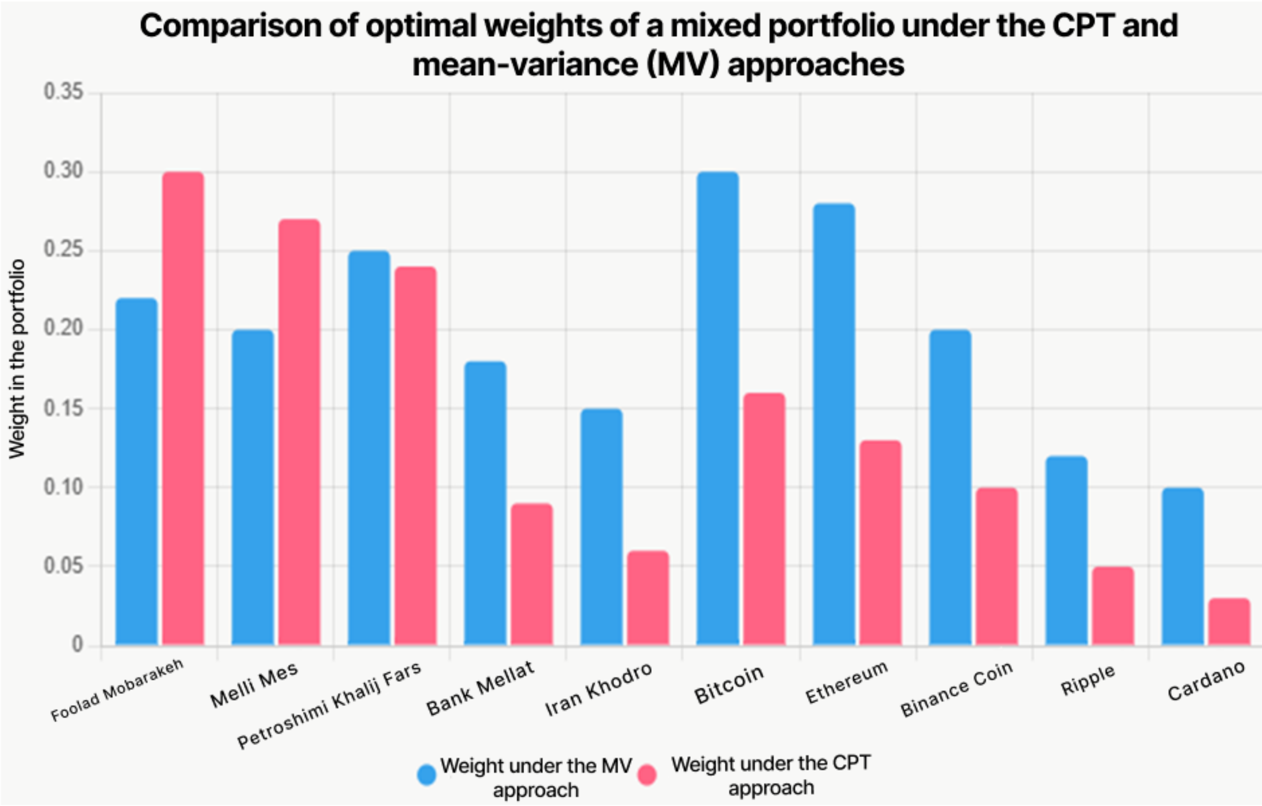

Figure 3: Comparison of optimal weights under MV and CPT approaches

Hypothesis Testing

Given that the research model simultaneously measures relationships among multiple latent variables (the main constructs of the study), Structural Equation Modeling (SEM) was employed to analyze the data and test the hypotheses. In this study, to obtain more precise results, the Partial Least Squares (PLS) method was used to test the conceptual model. PLS is a variance-based path modeling technique that enables the simultaneous examination of theory and measurement models (Fornell & Larcker, 1981). In this method, two models are evaluated: (1) the outer model, which examines the relationships between indicators (research items) and their respective latent variables, equivalent to the measurement model in covariance-based approaches; and (2) the inner model, which assesses the structural part of the model and is used to examine relationships among latent variables, from which the research hypotheses are derived.

Figure 4 presents the output of the measurement model for the research model extracted from the PLS software.

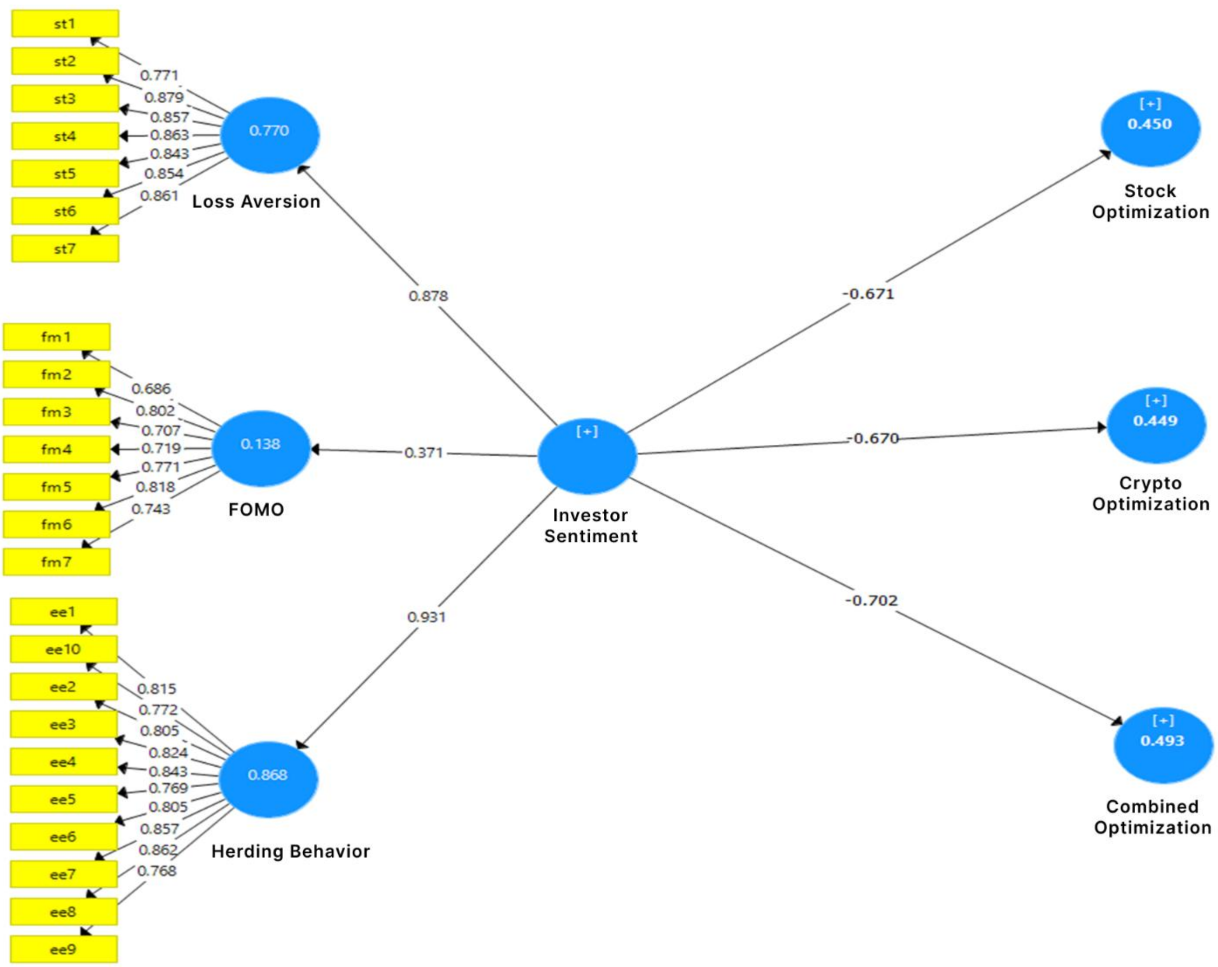

Figure 4: Measurement model output in SmartPLS software

Inner Model (Structural Model) of the Research Hypotheses

According to the PLS data analysis algorithm, after assessing the fit of the measurement model, the structural model is evaluated. Unlike the measurement model, the structural model does not deal with observed variables; rather, it focuses solely on latent variables and the relationships among them. The structural model examines the relationships between constructs. For this purpose, the Bootstrapping procedure was employed. The statistical sample size in this study was 384, and 500 bootstrap samples were used. Figure 5 illustrates the output of the structural model.

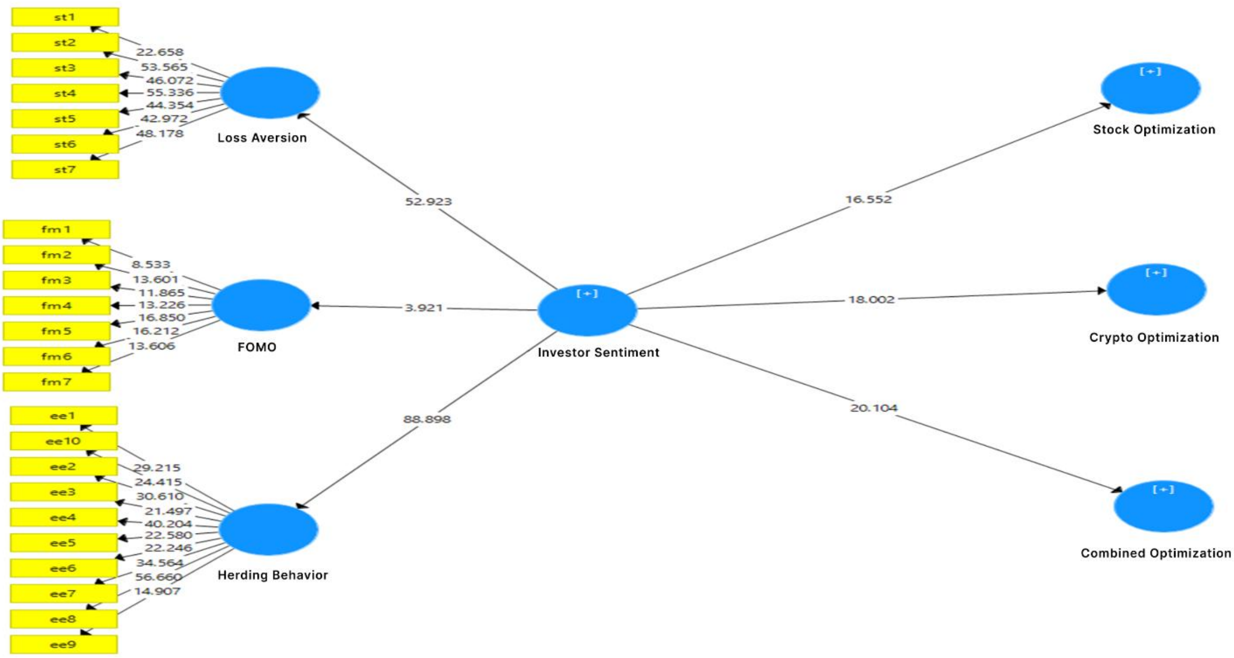

Figure 5: Structural model output in SmartPLS software

The numerical values displayed on the paths represent the t-statistics (t-values), which serve as the primary criterion for hypothesis acceptance or rejection. Acceptable threshold values for significance of path coefficients at confidence levels of 90%, 95%, and 99% are $t > 1.64$, $t > 1.96$, and $t > 2.57$, respectively (Mohsenin & Esfandiari, 2014). Based on these criteria, the model of the main hypotheses for the t-statistic is presented.

Results of Hypothesis Testing

Hypothesis 1: Investor sentiment has a combined effect on portfolio optimization in stock and cryptocurrency markets.

Table 8. Path analysis results for Hypothesis 1

Path	Path Coefficient (β)	t-value	p-value	Significance
Investor Sentiment → Combined Portfolio Optimization	-0.702	20.104	0.000	Negative and significant

In this study, portfolio optimization is defined as the CPT value of the optimal portfolio relative to the equal-weighted portfolio. Based on the PLS-SEM results, the path from investor sentiment to combined portfolio optimization (stocks + cryptocurrencies) has a t-value of 20.104, which is substantially greater than the critical value of 2.57, indicating significance at the 99% confidence level ($p < 0.01$). The path coefficient ($\beta = -0.702$) indicates a negative and significant effect of investor sentiment on portfolio optimization; specifically, a one-unit increase in investor sentiment leads, on average, to a 0.702-unit decrease in combined portfolio optimization.

From a behavioral perspective, this finding implies that the presence of stronger emotional biases (such as FOMO, herding behavior, and loss aversion) reduces the capacity for rational and optimal decision-making in asset allocation. Therefore, Hypothesis 1 is supported.

Hypothesis 2: Investor sentiment affects portfolio optimization in the stock market.

Table 9. Path analysis results for Hypothesis 2

Path	Path Coefficient (β)	t-value	p-value	Significance
Investor Sentiment → Stock Portfolio Optimization	-0.671	16.552	0.000	Negative and significant

According to the PLS-SEM results, the t-value for the path from investor sentiment to stock portfolio optimization is 16.552, which exceeds the critical value of 2.57 and is significant at the 99% confidence level ($p < 0.01$). The path coefficient ($\beta = -0.671$) indicates a negative and significant effect of investor sentiment on portfolio optimization in the stock market. In other words, an increase in investor sentiment leads to a 0.671-unit reduction in the optimization of stock asset allocation. This finding suggests that investors with stronger emotional tendencies exhibit lower capability in risk management, rational asset selection, and optimal diversification in the stock market. Therefore, Hypothesis 2 is also supported.

Hypothesis 3: Investor sentiment affects portfolio optimization in the cryptocurrency market.

Table 10. Path analysis results for Hypothesis 3

Path	Path Coefficient (β)	t-value	p-value	Significance
Investor Sentiment → Cryptocurrency Portfolio Optimization	-0.670	18.002	0.000	Negative and significant

The PLS-SEM results indicate that the t-value for the path from investor sentiment to cryptocurrency portfolio optimization is 18.002, which is significantly greater than the critical value of 2.57, confirming significance at the 99% confidence level ($p < 0.01$). The path coefficient ($\beta = -0.670$) demonstrates that investor sentiment has a negative and significant effect on the ability to optimize digital asset allocation. Specifically, with an increase in investor sentiment, cryptocurrency portfolio optimization decreases by an average of 0.670 units. Given the high volatility and emotionally driven environment of cryptocurrency markets, the magnitude of this negative effect is substantial. Therefore, Hypothesis 3 is supported.

Hypothesis 4: The effect of investor sentiment on portfolio optimization is stronger in the cryptocurrency market than in the stock market.

Table 11. Correlation matrix results for Hypothesis 4

Constructs	1	2	3	4	5	6	7
1. Investor Sentiment	1	-0.62	-0.65	-0.69	0.41	0.88	0.82
2. Stock Optimization	-0.62	1	0.71	0.79	-0.28	-0.51	-0.49
3. Crypto Optimization	-0.65	0.71	1	0.83	-0.33	-0.54	-0.47
4. Combined Optimization	-0.69	0.79	0.83	1	-0.36	-0.57	-0.52
5. FOMO	0.41	-0.28	-0.33	-0.36	1	0.49	0.45
6. Herding Behavior	0.88	-0.51	-0.54	-0.57	0.49	1	0.71
7. Loss Aversion	0.82	-0.49	-0.47	-0.52	0.45	0.71	1

Based on the correlation matrix, investor sentiment exhibits the strongest relationships with behavioral components such as herding behavior and loss aversion. The correlation between investor sentiment and herding behavior is 0.88, and between investor sentiment and loss aversion is 0.82, indicating that these two components contribute most significantly to the formation of investor sentiment. Additionally, the correlation between investor sentiment and FOMO is 0.41, which, although lower in magnitude than the previous two variables, still represents a meaningful positive association, suggesting that psychological pressure arising from investment opportunities is also influenced by emotional tendencies.

On the other hand, the relationships between investor sentiment and portfolio optimization indicators across stock, cryptocurrency, and combined markets are negative and relatively strong. The correlations are -0.62 for stock optimization, -0.65 for cryptocurrency optimization, and -0.69 for combined optimization. These values indicate that increasing emotional bias reduces investors' ability to optimally allocate assets and manage risk. In essence, the presence of emotional biases is associated with a decline in rational and logical decision-making processes, which is consistent with behavioral finance theories and classical portfolio optimization models such as the Markowitz model.

Furthermore, the results indicate that optimization components across the three scenarios are positively and relatively strongly correlated. The correlation between stock and cryptocurrency optimization is 0.71, between stock and combined optimization is 0.79, and between cryptocurrency and combined optimization is 0.83. This is expected, as investors exhibiting more rational, risk-managed behavior tend to perform optimally across both markets. Additionally, FOMO shows a negative correlation with portfolio optimization, with values of -0.28 and -0.33 for stock and cryptocurrency markets, respectively, indicating that psychological pressure from fear of missing out can impair optimal investment performance.

4. Discussion and Conclusion

The findings of this study provide strong empirical support for the central proposition of behavioral finance that investor sentiment significantly influences portfolio optimization outcomes, particularly in environments characterized by high volatility and informational uncertainty. The results obtained from the PLS-SEM analysis revealed that investor sentiment exerts a negative and statistically significant effect on portfolio optimization across all examined scenarios, including stock-only, cryptocurrency-only, and combined portfolios. The magnitude of this effect was substantial, with path coefficients indicating that increases in emotional biases such as loss aversion, herding behavior, and fear of missing out (FOMO) lead to a pronounced deterioration in optimization efficiency. These findings are consistent with prior research demonstrating that behavioral biases systematically distort rational decision-making processes and lead to suboptimal asset allocation [2, 3].

More specifically, the negative relationship between investor sentiment and portfolio optimization aligns with theoretical expectations derived from behavioral finance models, which emphasize that investors do not evaluate risk and return objectively but rather through psychologically biased lenses. The observed reduction in portfolio efficiency as sentiment increases can be attributed to the tendency of investors to overweight potential losses and underweight long-term expected returns, resulting in conservative or misaligned investment strategies. This interpretation is supported by empirical evidence indicating that sentiment-driven investors exhibit lower diversification efficiency and higher susceptibility to market noise [15, 28]. Furthermore, the findings corroborate studies conducted in emerging markets, where sentiment effects are often amplified due to weaker informational efficiency and higher participation of individual investors [7, 9].

The results also demonstrate that the impact of investor sentiment is not uniform across markets, with stronger effects observed in the cryptocurrency market compared to the stock market. This finding is particularly noteworthy and provides empirical support for the hypothesis that behavioral biases exert greater influence in highly volatile and speculative environments. Cryptocurrency markets, by their nature, are more susceptible to emotional trading due to the absence of intrinsic valuation anchors and the dominance of speculative dynamics. Prior studies have highlighted that cryptocurrency prices are heavily influenced by investor mood, social media activity, and narrative-driven behavior [11, 12]. The present findings extend this literature by demonstrating that such sentiment-driven dynamics not only affect price movements but also significantly impair portfolio optimization processes.

In addition, the stronger negative effect of sentiment in the cryptocurrency market can be explained by the higher levels of loss aversion observed among crypto investors. The estimated CPT parameters indicated that loss aversion coefficients were significantly higher in the cryptocurrency market, reflecting heightened sensitivity to potential losses. This is consistent with previous research showing that investors in highly volatile markets tend to exhibit stronger emotional reactions to downside risks, leading to defensive and sometimes irrational decision-making [22, 23]. As a result, portfolio allocations in such environments become more conservative and less efficient from a traditional optimization perspective.

Another important finding of this study is the divergence between portfolios optimized under behavioral frameworks and those derived from classical mean–variance models. The results indicated that CPT-based portfolios, although characterized by lower expected returns and Sharpe ratios, generated higher subjective value for investors. This outcome highlights the fundamental difference between normative and descriptive approaches to portfolio optimization. While classical models prioritize objective performance metrics, behavioral models account for investor preferences and psychological well-being, leading to investment strategies that may sacrifice some return in exchange for reduced exposure to extreme losses. This finding is in line with recent research emphasizing the importance of incorporating behavioral preferences into optimization models to better reflect real-world decision-making processes [17, 19].

Moreover, the results of the Monte Carlo simulation and Copula-GARCH modeling provide further insights into the role of dependence structures and tail risk in portfolio optimization. The findings demonstrated that ignoring tail dependence leads to significant underestimation of risk, particularly in cryptocurrency markets. This result reinforces the argument that traditional models based on normal distribution assumptions are inadequate for capturing the complex dynamics of modern financial markets. Previous studies have similarly highlighted the importance of modeling heavy tails and extreme co-movements in asset returns to improve risk assessment and portfolio performance [20, 21]. By integrating these advanced modeling techniques with behavioral frameworks, the present study offers a more comprehensive approach to portfolio optimization.

The observed positive correlations among optimization performance across different market segments also provide valuable insights into investor behavior. The results suggest that investors who demonstrate rational and disciplined decision-making in one market are likely to exhibit similar behavior in other markets. This finding is consistent with the notion that behavioral traits are relatively stable across contexts and can influence investment outcomes in a systematic manner [5, 6]. At the same time, the negative correlations between FOMO and portfolio optimization highlight the detrimental effects of emotionally driven decision-making, particularly in fast-moving and speculative markets. This aligns with prior evidence indicating that FOMO can lead to impulsive trading and suboptimal investment performance [14].

Furthermore, the study contributes to the growing body of literature on multi-market portfolio optimization by demonstrating the importance of considering cross-market behavioral dynamics. The findings indicate that sentiment spillover effects between stock and cryptocurrency markets can influence portfolio performance, supporting previous research on interconnected financial systems [16]. This highlights the need for integrated modeling approaches that capture both financial and behavioral linkages across markets.

The implications of these findings are particularly relevant for investors, portfolio managers, and policymakers. For investors, the results underscore the importance of recognizing and mitigating behavioral biases in order to improve decision-making and investment outcomes. For portfolio managers, the findings suggest that incorporating behavioral parameters into optimization models can enhance portfolio performance and better align investment strategies with client preferences. For policymakers, understanding the role of sentiment in financial markets can inform the design of regulatory frameworks aimed at reducing market inefficiencies and protecting investors.

Overall, the findings of this study provide robust empirical evidence supporting the integration of behavioral finance into portfolio optimization frameworks. By combining advanced econometric modeling with behavioral insights, the study offers a more realistic and comprehensive understanding of investment decision-making in modern financial markets. The results highlight the limitations of traditional models and demonstrate the value of incorporating psychological factors into financial analysis, particularly in the context of increasingly complex and interconnected markets [13, 24].

One of the key contributions of this study is its ability to bridge the gap between theoretical models and practical applications. While behavioral finance has long emphasized the importance of psychological factors, its integration into quantitative models has remained limited. The present study addresses this gap by operationalizing behavioral constructs within a rigorous mathematical framework and demonstrating their impact on portfolio optimization. This approach not only enhances the explanatory power of financial models but also provides actionable insights for practitioners.

The findings also highlight the evolving nature of financial markets and the increasing importance of interdisciplinary approaches in financial research. As markets become more complex and influenced by technological and social factors, traditional models must be adapted to incorporate new sources of information and behavioral dynamics. The integration of sentiment analysis, machine learning, and advanced statistical techniques represents a promising direction for future research and practice [18, 24].

Despite its contributions, this study is subject to several limitations that should be acknowledged. First, the behavioral data were collected through self-reported questionnaires, which may be subject to response biases and limitations in capturing true psychological states. Second, the study focused on a specific set of assets within the Tehran Stock Exchange and cryptocurrency markets, which may limit the generalizability of the findings to other markets or asset classes. Third, the modeling framework, while comprehensive, relies on certain assumptions regarding distributional properties and parameter estimation that may not fully capture the complexity of real-world markets.

Future research can build on the findings of this study by exploring additional behavioral factors and their impact on portfolio optimization. For example, incorporating variables such as overconfidence, ambiguity aversion, and time preferences could provide a more comprehensive understanding of investor behavior. Additionally, extending the analysis to other financial markets and asset classes would enhance the generalizability of the results. The use of high-frequency data and real-time sentiment indicators derived from social media and news sources could also improve the accuracy and relevance of behavioral models.

From a practical perspective, the results of this study suggest several important implications for investment management. Investors and portfolio managers should consider incorporating behavioral insights into their decision-making processes and risk management strategies. This may involve the use of behavioral diagnostics, training programs, and decision-support tools designed to mitigate the effects of emotional biases. Furthermore, the adoption of advanced modeling techniques that integrate behavioral and financial data can enhance portfolio performance and resilience in volatile market conditions.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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