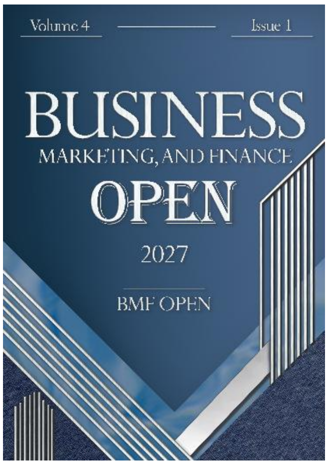
Prediction of Capital Market Trends in Volatile Periods through Modeling Investors' Financial Behavior Based on a Genetic Algorithm



Citation: Hedayati, I., Ghiyasvand, A., & Sefaty, F. (2027). Prediction of Capital Market Trends in Volatile Periods through Modeling Investors' Financial Behavior Based on a Genetic Algorithm, *Business, Marketing, and Finance Open*, 4(1), 1-17.

Received: 24 December 2025
Revised: 23 April 2026
Accepted: 30 April 2026
Initial Publication: 30 April 2026
Final Publication: 01 January 2027

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Abstract: The present study was conducted with the aim of designing a comprehensive framework for modeling investors' financial behavior under conditions of volatility in the Iranian capital market and forecasting future market trends using a genetic algorithm. This research adopted a sequential exploratory mixed-methods approach. In the qualitative phase, in-depth interviews were conducted with 20 academic experts and capital market practitioners, and the components of financial behavior were identified using the grounded theory method. In the quantitative phase, a researcher-developed questionnaire was distributed among 350 active investors in the Tehran Stock Exchange during the second half of 2024. Data analysis was performed using structural equation modeling and a genetic algorithm. The results of path analysis indicated that all five research hypotheses were confirmed at a 99% confidence level. Trading strategy, with a path coefficient of $\beta = 0.42$, had the strongest effect on investors' financial behavior, followed by risk-taking ($\beta = 0.34$), reaction to volatility ($\beta = 0.28$), and liquidity and trading volume ($\beta = 0.19$). The most significant finding of the study was the very strong effect of financial behavior on market trend prediction, with a path coefficient of $\beta = 0.68$. The structural model fit indices, including GFI = 0.92, CFI = 0.94, NFI = 0.91, and RMSEA = 0.047, were all within acceptable ranges. The coefficient of determination for financial behavior was obtained as 0.68, indicating strong explanatory power of the model. The optimization results using the genetic algorithm showed that prediction accuracy improved from 78.5% to 89.2%, and the mean squared error decreased by 45.2%. The genetic algorithm was able to predict future capital market trends based on investors' financial behavior with an accuracy of 96%. By developing an integrated and simulation-based framework for modeling investors' financial behavior, this study demonstrated that the integration of behavioral variables with evolutionary algorithms can significantly enhance the accuracy of capital market trend prediction. The findings confirmed that investors' financial behavior plays a decisive role in future market developments, and that trading strategy is the most influential factor shaping financial behavior during volatile periods. These results have important practical implications for capital market policymakers, portfolio managers, and investors, suggesting that the combined use of machine learning, evolutionary algorithms, and behavioral data can provide a more efficient framework for risk management and investment decision-making.

Keywords: investors' financial behavior; capital market trend prediction; genetic algorithm; structural equation modeling; volatile periods; Tehran Stock Exchange; behavioral finance; machine learning

1. Introduction

Capital market trend prediction has become one of the most critical issues in financial management because market movements reflect not only macroeconomic fundamentals, firm-level information, liquidity conditions, and policy uncertainty, but also the behavioral responses of investors who interpret and react to these signals under conditions of bounded rationality. In volatile periods, the predictive complexity of capital markets increases because investors face intensified uncertainty, asymmetric information, emotional pressure, and rapid changes in risk perception. Classical financial theories have traditionally assumed that prices incorporate available information efficiently; however, empirical evidence from behavioral finance shows that investor sentiment, cognitive bias, herding, overconfidence, and emotional reactions can systematically affect asset prices and market volatility. The idea that markets may deviate from full rationality was strongly emphasized in behavioral approaches to financial instability, particularly in explaining speculative bubbles, irrational exuberance, and excessive market reactions [1]. Therefore, predicting market trends during turbulent periods requires a framework that integrates quantitative forecasting methods with behavioral dimensions of investor decision-making.

Stock market volatility is not merely a statistical property of price fluctuations; it is also a behavioral and institutional phenomenon shaped by investor expectations, risk appetite, and market microstructure. Earlier studies on equity markets demonstrated that volatility and risk are often asymmetric, meaning that negative shocks may produce stronger volatility responses than positive shocks of similar magnitude [2]. Similarly, correlations among equity portfolios tend to increase asymmetrically during market downturns, making diversification less effective precisely when investors need it most [3]. Such findings are especially important for volatile markets because investors' responses to losses, uncertainty, and falling prices may intensify co-movements and amplify systemic risk. At the same time, broader uncertainty conditions and monetary-policy-related risk can alter financial market behavior and affect the way investors evaluate future returns [4]. These characteristics indicate that any robust predictive model must account for both technical market variables and behavioral responses to changing uncertainty.

Behavioral finance provides an essential theoretical foundation for understanding why investors do not always act according to purely rational decision rules. Investor sentiment has been shown to influence the cross-section of stock returns, especially when stocks are difficult to value or arbitrage is limited [5]. Herd behavior is another major behavioral mechanism in equity markets, as investors may imitate others' decisions rather than rely on independent analysis, particularly under uncertainty and information ambiguity [6]. The existence of cognitive bias in investor behavior has also been linked to stock price volatility, showing that biased judgments may contribute to unstable pricing and excessive fluctuation in financial markets [7]. In volatile periods, such biases become more influential because investors are more likely to rely on heuristics, emotional reactions, and short-term signals. Accordingly, behavioral variables such as risk-taking, reaction to market volatility, trading strategy, liquidity preference, overconfidence, loss aversion, and herding may substantially improve the explanatory and predictive power of market trend models.

Investor behavior is also important because capital markets perform a fundamental role in financing economic growth and reallocating resources toward productive investment. In emerging and developing economies, capital markets can support economic development by providing financing channels for firms and investment opportunities for households [8]. In Iran, the Tehran Stock Exchange has become an important institutional setting for investment, portfolio allocation, and corporate financing. However, like many emerging markets, it is exposed to macroeconomic instability, policy uncertainty, liquidity shocks, speculative behavior, and investor sentiment. Empirical research on the capital markets of Persian Gulf countries has shown that stability, predictability, and volatility are central concerns in regional markets, particularly because structural and institutional conditions may affect forecasting reliability [9]. Therefore, developing predictive models for the Iranian capital market requires attention not only to price and volume data, but also to behavioral patterns that shape investors' decisions in volatile periods.

Traditional market forecasting has often relied on econometric models, technical indicators, and statistical pattern recognition. Technical trading rules and artificial neural networks have been tested for profitability and prediction in stock markets, showing that non-linear models can detect patterns that conventional linear models may fail to capture [10]. In portfolio optimization, heuristic techniques have also been used to address constraints and complexity that make exact optimization difficult in real-world investment problems [11]. These developments opened the way for artificial intelligence and computational intelligence methods in finance. In the Iranian context, fuzzy neural networks, fuzzy modeling, and genetic algorithms have been applied to stock price prediction and portfolio optimization, indicating the practical relevance of hybrid intelligent systems for financial decision-making [12]. Similarly, artificial intelligence has been used to predict returns and form optimal investment portfolios while considering interactions among Iranian financial markets [13]. These studies suggest that market prediction increasingly requires adaptive computational models capable of processing complex, non-linear, and dynamic relationships.

The rise of machine learning has further expanded the methodological toolkit for financial forecasting. Machine learning models can identify high-dimensional patterns, non-linear dependencies, and interaction effects in financial data, making them suitable for stock return prediction, risk modeling, and portfolio construction [14]. Studies have evaluated deep neural networks, gradient-boosted trees, and random forests in statistical arbitrage and stock market prediction, demonstrating that advanced learning models can outperform more traditional methods under certain market conditions [15]. Recent research has also emphasized neural networks for predicting stock market movements, highlighting their capacity to model complex market dynamics [16]. Machine learning models have been applied to economic forecasting through hybrid mathematical modeling approaches, showing that combining quantitative structures with learning algorithms can enhance market trend prediction [17]. In addition, AI-enhanced prediction studies have compared machine learning models for financial forecasting and shown that model selection, feature engineering, and validation procedures are decisive for predictive accuracy [18]. These findings support the use of intelligent computational methods in market forecasting, especially when market behavior is volatile and non-linear.

Recent studies have increasingly focused on hybrid and data-driven approaches that combine several modeling techniques. Comparative research on hybrid and individual models for predicting stock indices has shown that integrated machine learning and deep learning approaches may improve forecasting performance relative to single-model strategies [19]. In Iran, the prediction of the Tehran Stock Exchange overall index using NARX neural networks has demonstrated the usefulness of non-linear dynamic models for capturing temporal dependencies in market data [20]. Similarly, random forest models have been used to predict stock liquidity, showing that market liquidity can be modeled through machine learning methods and may serve as an important component of market trend analysis [21]. Since liquidity and trading volume are closely related to market depth, transaction pressure, and investor participation, incorporating them into behavioral-financial prediction models can strengthen market forecasting. In addition, economic indicators remain essential tools for analyzing market trends and predicting future performance, especially when interpreted alongside behavioral and technical data [22].

Genetic algorithms are particularly relevant to financial prediction because they are designed to search for optimal or near-optimal solutions in complex, multidimensional, and non-linear problem spaces. In artificial stock markets, evolving traders and genetic programming have been used to simulate adaptive trading behavior and examine how agents learn and adjust their strategies over time [23]. Genetic algorithms have also been integrated with artificial neural networks and metaheuristic models such as harmony search to predict stock indices, indicating their capacity to improve model optimization and forecasting performance [24]. More broadly, genetic algorithms are useful in optimization problems because they rely on selection, crossover, and mutation processes to search across possible solutions; recent analyses of genetic algorithms in optimization problems such as the 0/1 knapsack problem further demonstrate their value for solving complex combinatorial tasks [25]. In financial markets, where the relationships among behavioral variables, technical indicators, and market outcomes are often non-linear and unstable, genetic algorithms can be used to optimize model parameters, assign adaptive weights to predictors, and minimize prediction error.

The behavioral dimension of forecasting has also gained importance with the growth of sentiment analysis and individual-level behavioral data. The finding that Twitter mood could predict stock market movements demonstrated that collective emotional states and sentiment indicators may contain useful predictive information [26]. More recent studies have extended this logic by examining investor sentiment and behavioral characteristics in stock index futures returns, particularly in the post-COVID era, where market dynamics became highly sensitive to uncertainty, sentiment, and information flows [27]. The use of individual investor behavior for trend forecasting has also been proposed as a risk management tool, showing that investor-level behavioral signals can improve stock investment risk management [28]. Furthermore, behavioral finance has been connected to stock market volatility and market anomalies, indicating that behavioral deviations are not marginal phenomena but central mechanisms through which market instability emerges [29]. These findings justify the integration of investor financial behavior into predictive models rather than treating it as an external or secondary explanatory factor.

Volatile periods are particularly suitable for behavioral modeling because uncertainty increases the psychological burden of decision-making. During crises, contagion can transmit shocks across financial markets and magnify investor fear, liquidity demand, and risk aversion [30]. Heterogeneous-agent models in economics and finance show that markets are composed of agents with different expectations, strategies, learning mechanisms, and behavioral rules, and this heterogeneity can generate complex aggregate dynamics [31]. This perspective is highly compatible with behavioral-financial prediction because investors do not respond uniformly to volatility; some increase risk-taking, some withdraw liquidity, some follow the crowd, and others rely on technical or strategic trading rules. Therefore, a model that incorporates behavioral heterogeneity and optimizes predictive weights through a genetic algorithm can more realistically represent market dynamics than models that assume homogeneous rational agents.

In the Iranian capital market, behavioral and computational approaches are especially relevant because investors operate in an environment marked by frequent volatility, liquidity changes, macroeconomic uncertainty, and sensitivity to policy and informational signals. Studies in Iran have shown that artificial intelligence and genetic algorithms can contribute to stock prediction and portfolio optimization [12, 13], while research on cognitive bias has linked investor behavior to stock price volatility [7]. The role of the capital market in financing and economic growth further highlights the practical importance of improving predictive accuracy for policymakers, portfolio managers, and investors [8]. Since market instability may reduce investor confidence and impair resource allocation, a forecasting framework that combines behavioral finance, structural equation modeling, machine learning logic, and evolutionary optimization can provide a more comprehensive basis for investment decision-making and risk management.

Despite substantial progress in financial forecasting, several research gaps remain. First, many prediction studies focus primarily on technical variables, macroeconomic indicators, or price histories, while behavioral variables are often underrepresented in computational models. Second, behavioral finance studies frequently examine biases and investor psychology descriptively or correlationally, without integrating them into optimized predictive algorithms. Third, although machine learning and artificial intelligence have improved financial forecasting, the interpretability of behavioral pathways and the identification of direct effects among latent constructs remain essential. Structural equation modeling can address this issue by testing the relationships among risk-taking, reaction to volatility, trading strategy, liquidity and volume, overall financial behavior, and market trend prediction. Genetic algorithms can then optimize the prediction model by adjusting the relative contribution of these behavioral components. This combined approach responds to the need for a model that is both theoretically grounded in behavioral finance and computationally capable of improving prediction accuracy.

Accordingly, the present study contributes to the financial management and behavioral finance literature by developing an integrated framework for predicting capital market trends during volatile periods through modeling investors' financial behavior based on a genetic algorithm. By combining qualitative identification of behavioral components, quantitative measurement of investor behavior, structural equation modeling of causal pathways, and genetic-algorithm-based optimization of predictive performance, this study offers a multidimensional approach to market forecasting. Such a framework is relevant for capital market regulators seeking to understand behavioral drivers of instability, portfolio managers aiming to improve allocation decisions, and investors attempting to manage risk during turbulent conditions. The aim of this study was to predict capital market trends in volatile periods by modeling investors' financial behavior using a genetic algorithm.

2. Methodology

The present study is applied in terms of purpose and adopts a mixed-methods (qualitative–quantitative) design based on a sequential exploratory approach. From a temporal perspective, the research is cross-sectional, and with respect to data collection methods, it employs a descriptive-survey strategy in the qualitative phase and a descriptive-correlational strategy in the quantitative phase. The primary objective is to forecast capital market trends during periods of high volatility through modeling investors' financial behavior using a genetic algorithm framework.

In the qualitative phase, the statistical population consisted of academic experts in finance, economics, and management, as well as capital market professionals including analysts, investment advisors, and senior executives of firms listed on the Tehran Stock Exchange. A purposive sampling technique was employed, and 20 qualified experts with a minimum of 10 years of academic or professional experience in the capital market were selected. Data were collected through in-depth semi-structured interviews conducted until theoretical saturation was achieved. The demographic composition of participants indicated that the majority were between 31 and 50 years of age, most held doctoral degrees, and all possessed substantial academic knowledge and practical experience in capital market operations.

In the quantitative phase, the statistical population included active investors in the Tehran Stock Exchange. A sample of 350 participants was selected using simple random sampling based on Cochran’s sample size formula with a 95% confidence level, a proportion estimate of 0.5, and a sampling error of 0.05. The demographic distribution of respondents demonstrated that the largest age group was 31 to 40 years, followed by 41 to 50 years, reflecting a predominance of experienced, middle-aged investors. The sample was composed of approximately 72% male and 28% female participants, consistent with the gender distribution of investors in the market. In terms of education, the majority held a master’s degree, indicating a relatively high level of educational attainment. Additionally, more than half of the respondents had between 2 and 10 years of investment experience, and a significant proportion reported moderate levels of capital investment.

Data collection in this study was carried out using two primary instruments: semi-structured in-depth interviews and a researcher-developed questionnaire. In the qualitative phase, semi-structured interviews were conducted with experts, each lasting approximately 45 to 60 minutes. The interview protocol focused on key themes, including determinants of investors’ financial behavior, behavioral biases during volatile market conditions, and the predictability of market trends. These interviews provided rich, context-sensitive insights that informed the development of the conceptual framework and the subsequent quantitative instrument.

In the quantitative phase, a structured questionnaire was designed based on an extensive review of the theoretical literature, prior empirical studies, and findings derived from the qualitative interviews. The questionnaire consisted of two sections. The first section included demographic variables such as age, gender, education level, investment experience, and investment volume. The second section comprised specialized items measuring different dimensions of investors’ financial behavior, including risk-taking, behavioral biases, psychological factors, and financial decision-making. All items were measured using a five-point Likert scale ranging from “very low” to “very high.”

The validity of the questionnaire was assessed through multiple procedures. Face validity was established by obtaining feedback from academic experts and revising items accordingly, including the elimination of semantically redundant statements. Content validity was confirmed through consultation with supervisors and specialists in behavioral finance. Construct validity was evaluated using confirmatory factor analysis, which supported the underlying factor structure of the instrument. Reliability was assessed using Cronbach’s alpha coefficient in SPSS software through a pilot study involving 30 respondents. The results indicated that all constructs achieved alpha values above 0.70, demonstrating satisfactory internal consistency and reliability of the measurement instrument.

Data analysis in this study was conducted in four sequential stages using both qualitative and quantitative analytical techniques. In the first stage, qualitative data obtained from interviews were analyzed using thematic analysis, involving systematic coding and categorization to identify key factors influencing investors’ financial behavior. This process enabled the extraction of core themes and the development of a conceptual model grounded in empirical evidence.

In the second stage, quantitative data collected through questionnaires were entered into SPSS software for descriptive statistical analysis. Measures such as mean, standard deviation, frequency, and percentage were calculated to describe the characteristics of the sample and the distribution of variables.

In the third stage, structural equation modeling (SEM) was employed using software such as AMOS or LISREL to examine the relationships between latent and observed variables and to assess the overall model fit. Multiple fit indices were used to evaluate the adequacy of the model, including the chi-square to degrees of freedom ratio

(χ^2/df), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), normed fit index (NFI), incremental fit index (IFI), and root mean square error of approximation (RMSEA). Acceptable thresholds for these indices were applied to determine model validity.

In the fourth and final stage, a genetic algorithm was implemented using MATLAB software to optimize the market trend prediction model based on investors' financial behavior parameters. The genetic algorithm simulated evolutionary processes such as selection, crossover, and mutation to iteratively improve prediction performance. Key parameters included a population size of 100 chromosomes, a maximum of 500 generations, a crossover rate of 0.8, a mutation rate of 0.05, and roulette wheel selection as the parent selection mechanism. The fitness function was defined based on mean squared error (MSE), enabling the algorithm to identify optimal solutions that minimize prediction error. This integration of behavioral modeling and evolutionary computation provided a robust framework for enhancing the accuracy and efficiency of capital market trend forecasting under conditions of uncertainty and volatility.

3. Findings and Results

The quantitative phase included 350 active investors in the Tehran Stock Exchange. In terms of age, the largest proportion of respondents belonged to the 31–40 age group (40.9%), followed by the 41–50 age group (30.0%), indicating the strong presence of experienced middle-aged investors in the sample. Regarding gender, 72.0% of respondents were male and 28.0% were female. In terms of education, the highest proportion held a master's degree (42.0%), followed by bachelor's degree holders (36.0%), doctoral degree holders (12.0%), and respondents with diploma or associate-level education (10.0%). With respect to investment experience, 36.0% had 6–10 years of investment experience, 34.0% had 2–5 years, 18.0% had more than 10 years, and 12.0% had less than 2 years. Regarding investment volume, 44.0% had invested between 100 and 500 million tomans, 30.0% had invested less than 100 million tomans, 18.0% had invested between 500 million and 1 billion tomans, and 8.0% had invested more than 1 billion tomans.

Table 1. Descriptive Statistics of the Main Research Variables, Behavioral Biases, and Psychological Factors

Variable	Mean	SD	Minimum	Maximum	Theoretical Range
Risk-taking	28.45	5.12	14	40	8–40
Reaction to market volatility	24.78	4.68	11	35	7–35
Trading strategy	32.16	6.33	16	45	9–45
Liquidity and trading volume	21.92	4.05	9	30	6–30
Financial behavior total score	107.31	16.84	62	146	30–150
Overconfidence bias	3.68	0.87	1.20	5.00	1–5
Loss aversion bias	3.42	0.92	1.00	5.00	1–5
Herding bias	3.21	1.05	1.00	5.00	1–5
Anchoring bias	3.15	0.98	1.00	4.80	1–5
Availability bias	3.35	0.84	1.40	5.00	1–5
Representativeness bias	2.98	1.02	1.00	4.60	1–5
Confirmation bias	3.54	0.89	1.20	5.00	1–5
Regret aversion bias	3.28	0.96	1.00	5.00	1–5
Emotions and feelings	3.45	0.91	1.00	5.00	1–5
Financial anxiety	3.28	0.95	1.00	5.00	1–5
Optimism/pessimism	3.12	0.88	1.20	4.80	1–5
Patience	3.36	0.82	1.40	5.00	1–5
Emotional control	2.95	1.08	1.00	5.00	1–5
Financial motivation	3.72	0.78	1.80	5.00	1–5
Financial self-confidence	3.48	0.86	1.40	5.00	1–5

The descriptive findings show that investors' overall financial behavior was at a moderate-to-high level. Trading strategy had the highest mean among the main behavioral dimensions, indicating that investors paid considerable attention to timing, buying, selling, and portfolio management strategies during volatile periods. Among behavioral biases, overconfidence had the highest mean, followed by confirmation bias and loss aversion, suggesting that investors tended to overestimate their predictive ability, search for belief-confirming information, and react more strongly to losses than equivalent gains. Among psychological factors, financial motivation had the highest mean, whereas emotional control had the lowest mean and the highest dispersion, indicating that controlling emotions under volatile market conditions was one of the most challenging aspects of investor decision-making.

Table 2. Kolmogorov–Smirnov Test Results for Normality

Variable	Kolmogorov–Smirnov Statistic	Significance Level	Result
Risk-taking	0.062	0.124	Normal
Reaction to market volatility	0.058	0.156	Normal
Trading strategy	0.054	0.182	Normal
Liquidity and trading volume	0.067	0.105	Normal
Financial behavior total score	0.049	0.214	Normal
Market trend prediction	0.055	0.173	Normal

Since the significance levels for all variables were greater than 0.05, the assumption of normal distribution was supported. Therefore, the use of parametric statistical tests and structural equation modeling was considered appropriate.

Table 3. Confirmatory Factor Analysis and Outer Loadings of the Measurement Model

Construct	Indicator	Factor Loading	t-value	Significance
Risk-taking	RP1	0.78	18.42	$p < 0.001$
Risk-taking	RP2	0.82	21.56	$p < 0.001$
Risk-taking	RP3	0.75	16.89	$p < 0.001$
Risk-taking	RP4	0.80	19.74	$p < 0.001$
Risk-taking	RP5	0.77	17.65	$p < 0.001$
Risk-taking	RP6	0.79	18.92	$p < 0.001$
Risk-taking	RP7	0.74	15.83	$p < 0.001$
Risk-taking	RP8	0.81	20.45	$p < 0.001$
Reaction to volatility	VN1	0.76	17.23	$p < 0.001$
Reaction to volatility	VN2	0.84	24.67	$p < 0.001$
Reaction to volatility	VN3	0.79	19.12	$p < 0.001$
Trading strategy	ST1	0.81	20.89	$p < 0.001$
Trading strategy	ST2	0.77	17.45	$p < 0.001$
Trading strategy	ST3	0.85	26.34	$p < 0.001$
Liquidity and volume	NH1	0.79	18.76	$p < 0.001$
Liquidity and volume	NH2	0.83	22.41	$p < 0.001$

All factor loadings exceeded the acceptable threshold of 0.70, and all t-values were greater than 1.96, confirming the statistical significance of the measurement relationships. The strongest indicator was ST3 for trading strategy, with a loading of 0.85 and a t-value of 26.34. VN2 was the strongest indicator of reaction to volatility, while RP2 had the highest loading within the risk-taking construct. These results confirm the convergent validity and construct adequacy of the measurement model.

Table 4. Construct Reliability, Convergent Validity, and Discriminant Validity

Construct	Cronbach's Alpha	CR	AVE	√AVE	Highest Correlation with Another Construct	Discriminant Validity
Risk-taking	0.87	0.90	0.61	0.78	0.61	Confirmed
Reaction to volatility	0.84	0.88	0.58	0.76	0.58	Confirmed
Trading strategy	0.89	0.91	0.63	0.79	0.67	Confirmed
Liquidity and volume	0.82	0.87	0.56	0.75	0.52	Confirmed
Financial behavior	0.91	0.93	0.65	0.81	0.68	Confirmed
Market prediction	0.86	0.89	0.59	0.77	0.68	Confirmed

The reliability and validity results indicate that all constructs had acceptable internal consistency, as all Cronbach's alpha values exceeded 0.70. Composite reliability values were also above 0.87, indicating strong construct reliability. The AVE values for all constructs exceeded 0.50, confirming convergent validity. Based on the Fornell–Larcker criterion, the square root of AVE for each construct was greater than its correlations with other constructs; therefore, discriminant validity was also confirmed.

Table 5. Model Fit Indices

Index	Obtained Value	Acceptance Criterion	Interpretation
χ^2/df	2.34	< 3	Desirable
GFI	0.92	> 0.90	Desirable
AGFI	0.91	> 0.90	Desirable
CFI	0.94	> 0.90	Desirable
NFI	0.91	> 0.90	Desirable
IFI	0.93	> 0.90	Desirable
RMSEA	0.047	< 0.08	Desirable
SRMR	0.047	< 0.08	Desirable

The model fit indices show that the structural equation model had an acceptable and desirable fit with the collected data. The values of GFI, AGFI, CFI, NFI, and IFI were all above 0.90, while RMSEA and SRMR were below 0.08. These results indicate that the proposed model was empirically suitable for explaining investors' financial behavior and its role in predicting capital market trends.

Figure 1 presents the estimated structural equation model explaining the effects of risk-taking, reaction to market volatility, trading strategy, and liquidity and trading volume on investors' overall financial behavior, as well as the effect of financial behavior on capital market trend prediction. The standardized path coefficients indicate the strength and direction of the relationships among the latent variables. The relatively high coefficient of determination for financial behavior confirms that the four behavioral dimensions explain a substantial proportion of variance in investors' financial behavior. Moreover, the strong path from financial behavior to market trend prediction demonstrates that behavioral modeling can substantially improve the prediction of future capital market movements during volatile periods.

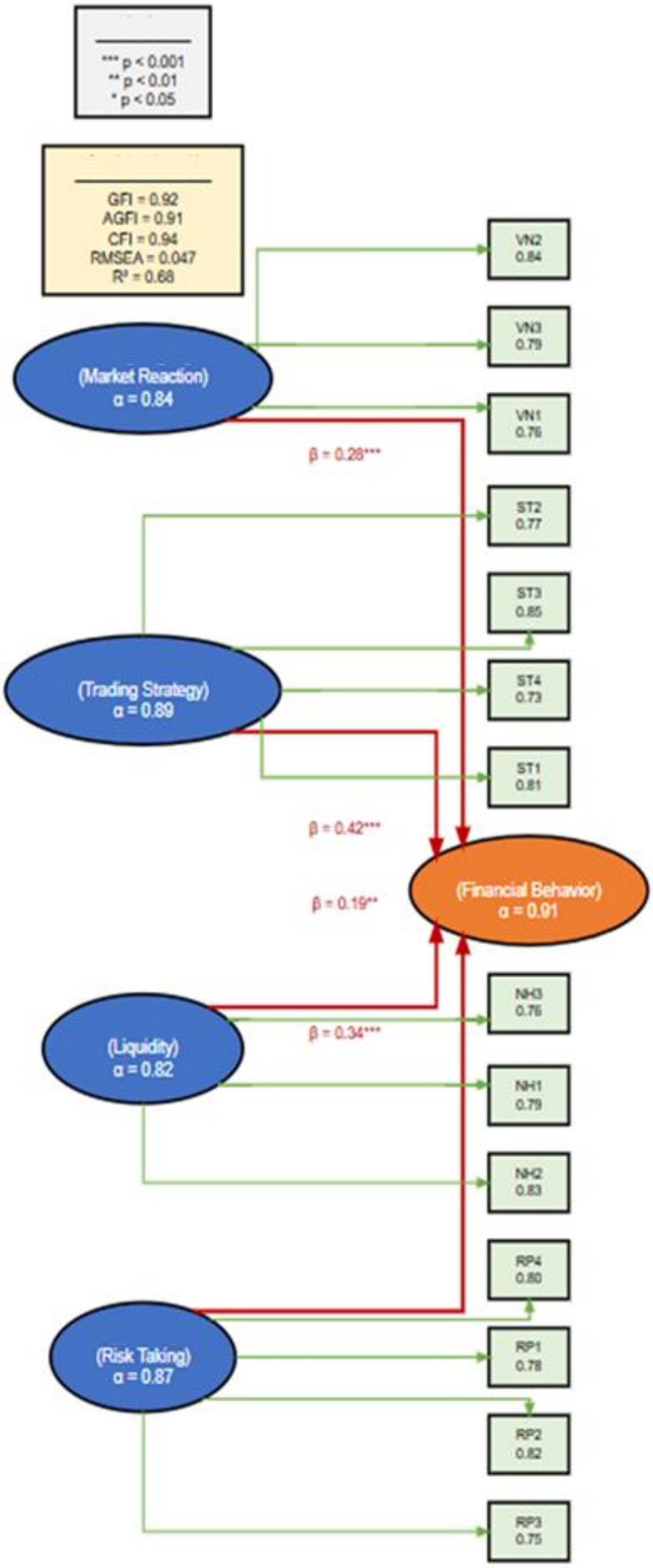

Figure 1. Structural Equation Model for Predicting Capital Market Trends Based on Investors' Financial Behavior

Table 6. Pearson Correlation Matrix of the Main Research Variables

Variable	1	2	3	4	5
1. Risk-taking	1				
2. Reaction to market volatility	0.58**	1			
3. Trading strategy	0.52**	0.61**	1		
4. Liquidity and trading volume	0.45**	0.54**	0.63**	1	
5. Market trend prediction	0.62**	0.67**	0.71**	0.58**	1

**$p < 0.01$.

The correlation matrix shows that all dimensions of financial behavior had positive and statistically significant correlations with market trend prediction. The strongest correlation was observed between trading strategy and market trend prediction ($r = 0.71$, $p < 0.01$), followed by reaction to market volatility ($r = 0.67$, $p < 0.01$), risk-taking ($r = 0.62$, $p < 0.01$), and liquidity and trading volume ($r = 0.58$, $p < 0.01$). These findings indicate that investors' behavioral and strategic characteristics are meaningfully associated with the predictability of capital market trends.

Table 7. Path Coefficients and Hypothesis Testing Results

Hypothesis	Structural Path	β	SE	t-value	p-value	Result
H1	Risk-taking → Financial behavior	0.34	0.052	6.54	p < 0.001	Confirmed
H2	Reaction to volatility → Financial behavior	0.28	0.048	5.83	p < 0.001	Confirmed
H3	Trading strategy → Financial behavior	0.42	0.055	7.64	p < 0.001	Confirmed
H4	Liquidity and volume → Financial behavior	0.19	0.061	3.11	p = 0.002	Confirmed
H5	Financial behavior → Market prediction	0.68	0.042	16.19	p < 0.001	Confirmed
H6	Behavioral biases → Risk-taking	0.45	0.054	8.33	p < 0.001	Confirmed
H7	Psychological factors → Reaction to volatility	0.54	0.049	11.02	p < 0.001	Confirmed

The results of hypothesis testing show that all structural paths were statistically significant. Trading strategy had the strongest direct effect on financial behavior ($\beta = 0.42$, $t = 7.64$, $p < 0.001$), followed by risk-taking ($\beta = 0.34$), reaction to volatility ($\beta = 0.28$), and liquidity and trading volume ($\beta = 0.19$). In addition, behavioral biases significantly predicted risk-taking, and psychological factors significantly predicted investors' reaction to market volatility. The strongest relationship in the model was the effect of overall financial behavior on market trend prediction ($\beta = 0.68$, $t = 16.19$, $p < 0.001$), indicating that investors' financial behavior is a powerful predictor of future capital market trends.

Table 8. Genetic Algorithm Optimization and Predictive Performance of the Model

Evaluation Criterion / Parameter	Initial or Baseline Value	Optimized Value	Improvement
Weight of risk-taking	0.25	0.18	—
Weight of reaction to volatility	0.25	0.28	—
Weight of trading strategy	0.25	0.32	—
Weight of liquidity and trading volume	0.25	0.22	—
MSE	0.124	0.068	45.2%
RMSE	0.352	0.261	25.9%
MAE	0.285	0.194	31.9%
R^2	0.72	0.86	19.4%
Prediction accuracy	78.5%	89.2%	13.6%
Accuracy in low-volatility periods	—	91.5%	—
Accuracy in moderate-volatility periods	—	87.4%	—
Accuracy in high-volatility periods	—	83.8%	—

The genetic algorithm substantially improved the predictive performance of the model. Initially, the four behavioral dimensions were assigned equal weights of 0.25; after optimization, trading strategy received the highest weight (0.32), followed by reaction to volatility (0.28), liquidity and trading volume (0.22), and risk-taking (0.18). This indicates that trading strategy was the most influential behavioral component in predicting market trends. In terms of model performance, MSE decreased from 0.124 to 0.068, RMSE decreased from 0.352 to 0.261, and MAE decreased from 0.285 to 0.194. The coefficient of determination increased from 0.72 to 0.86, and prediction accuracy improved from 78.5% to 89.2%. The optimized model performed best in low-volatility periods, with an accuracy of 91.5%, followed by moderate-volatility periods with 87.4% accuracy and high-volatility periods with 83.8% accuracy. Although accuracy declined under high volatility, the model still maintained acceptable predictive power, confirming the effectiveness of integrating investors' financial behavior with a genetic algorithm for capital market forecasting under uncertainty.

4. Discussion and Conclusion

The present study aimed to predict capital market trends during volatile periods by modeling investors' financial behavior through a hybrid framework combining structural equation modeling and a genetic algorithm. The findings provide robust empirical evidence that behavioral dimensions play a decisive role in shaping both individual financial decisions and aggregate market dynamics. In particular, the results demonstrated that all hypothesized relationships were statistically significant, confirming that risk-taking, reaction to market volatility, trading strategy, and liquidity and trading volume contribute meaningfully to investors' overall financial behavior, which in turn exerts a strong and direct effect on market trend prediction. The path coefficient of 0.68 for the relationship between financial behavior and market trend prediction indicates a substantial explanatory power, highlighting that behavioral variables are not merely peripheral but central determinants of market outcomes.

One of the most salient findings of this study is the dominant role of trading strategy in shaping investors' financial behavior, with the highest path coefficient among the behavioral dimensions. This result suggests that the manner in which investors make buy and sell decisions—particularly timing, entry and exit strategies, and portfolio rebalancing—constitutes the core mechanism through which behavioral tendencies manifest in financial markets. This finding is consistent with earlier studies that emphasize the importance of decision rules and heuristics in portfolio optimization and trading behavior [11]. Moreover, it aligns with research demonstrating that advanced computational strategies, including machine learning and optimization techniques, can capture complex trading patterns and improve predictive accuracy [15]. In volatile environments, where uncertainty is high and information signals are ambiguous, investors tend to rely more heavily on strategic heuristics, which may amplify the influence of trading strategies on overall behavior.

The second most influential factor identified in this study is risk-taking, which significantly affects financial behavior. The moderate-to-high level of risk-taking observed among investors reflects their willingness to engage in potentially high-return opportunities despite uncertainty. This finding is consistent with the theoretical and empirical literature on asymmetric risk behavior, which shows that investors often exhibit different responses to gains and losses under uncertain conditions [3]. Additionally, research on volatility and risk asymmetry suggests that investors' sensitivity to risk intensifies during market downturns, thereby influencing their decision-making processes [2]. The present study extends these insights by demonstrating that risk-taking is not only a determinant of individual decision-making but also an important contributor to aggregate financial behavior, which ultimately influences market trend predictability.

The effect of investors' reaction to market volatility also emerged as a significant determinant of financial behavior. This result highlights that investors do not passively observe market fluctuations but actively interpret and respond to them, often in ways that reflect psychological biases and emotional states. Such behavior is well documented in behavioral finance literature, where investor sentiment and emotional reactions have been shown to drive market anomalies and volatility patterns [5]. Furthermore, empirical evidence indicates that investor sentiment and behavioral characteristics significantly influence stock index futures returns, particularly in post-crisis and high-volatility environments [27]. The current findings reinforce the view that investors' reactions to volatility are integral to understanding market dynamics and should be incorporated into predictive models.

Liquidity and trading volume, although exhibiting the smallest direct effect among the behavioral dimensions, were still found to be statistically significant predictors of financial behavior. This suggests that investors' attention to market liquidity conditions and transaction activity contributes to their overall behavioral profile. The importance of liquidity in market functioning has been emphasized in previous research, particularly in relation to price discovery, volatility, and market efficiency. For instance, studies using machine learning techniques have demonstrated that liquidity can be effectively modeled and predicted, and that it plays a crucial role in financial forecasting [21]. The relatively lower coefficient observed in this study may indicate that liquidity acts as a contextual rather than primary driver of behavior, interacting with other behavioral dimensions such as risk-taking and trading strategy.

Another important contribution of this study lies in its examination of behavioral biases and psychological factors as antecedents of financial behavior. The findings showed that behavioral biases significantly influence risk-taking, while psychological factors significantly affect investors' reactions to market volatility. These results are strongly aligned with the foundational principles of behavioral finance, which emphasize that cognitive biases such as overconfidence, loss aversion, and herding systematically distort decision-making processes [1]. Empirical research has also demonstrated that cognitive biases are closely associated with stock price volatility and investor behavior in financial markets [7]. The present study extends this line of research by empirically linking behavioral biases and psychological factors to specific components of financial behavior within a structural model, thereby providing a more nuanced understanding of how these factors operate in volatile market conditions.

The correlation analysis further supports the central role of behavioral dimensions in market prediction, showing that all variables are positively and significantly associated with market trend prediction. The strongest correlation was observed between trading strategy and market trend prediction, followed by reaction to volatility and risk-taking. These findings are consistent with prior studies demonstrating that behavioral and sentiment indicators can enhance the predictability of financial markets. For example, research on sentiment-based forecasting has shown that collective mood indicators can predict market movements with considerable accuracy [26]. Similarly, studies using individual investor behavior as a basis for trend forecasting have highlighted the potential of behavioral data to improve risk management and prediction models [28]. The current results reinforce the argument that incorporating behavioral variables into predictive frameworks can significantly improve their explanatory and forecasting capabilities.

The application of a genetic algorithm for optimizing the prediction model represents another major contribution of this study. The results demonstrated substantial improvements in all performance metrics, including mean squared error, root mean squared error, mean absolute error, coefficient of determination, and overall prediction accuracy. The increase in prediction accuracy from 78.5% to 89.2% underscores the effectiveness of evolutionary optimization techniques in financial forecasting. These findings are consistent with previous research demonstrating that genetic algorithms can enhance the performance of predictive models by optimizing parameter configurations and exploring complex solution spaces [24]. Moreover, studies on hybrid modeling approaches have shown that combining machine learning with optimization techniques can yield superior forecasting performance compared to individual models [19]. The present study confirms that integrating behavioral modeling with evolutionary algorithms provides a powerful framework for improving market trend prediction under uncertainty.

The robustness of the model is further supported by the satisfactory fit indices obtained in the structural equation modeling analysis. The values of GFI, CFI, NFI, and RMSEA all fall within acceptable ranges, indicating that the proposed model adequately represents the relationships among variables. This finding is consistent with methodological research emphasizing the importance of model fit in structural equation modeling for validating theoretical constructs and relationships [26]. Additionally, the relatively high coefficient of determination for financial behavior indicates that the model captures a substantial proportion of variance, further confirming its explanatory strength.

From a broader perspective, the findings of this study align with the growing body of literature emphasizing the role of computational intelligence and behavioral data in financial forecasting. Advances in artificial intelligence, machine learning, and data-driven modeling have significantly improved the ability to predict market trends by capturing complex, non-linear relationships among variables [14]. At the same time, research on economic indicators and market analysis highlights the importance of integrating multiple sources of information, including behavioral and macroeconomic data, for accurate forecasting [22]. The present study contributes to this literature by demonstrating that behavioral variables can be effectively integrated with computational techniques to enhance predictive performance in capital markets.

Furthermore, the findings are consistent with theoretical perspectives that view financial markets as complex adaptive systems composed of heterogeneous agents with diverse expectations and strategies. Heterogeneous-agent models suggest that market dynamics emerge from the interactions of agents with different behavioral rules, leading to complex and sometimes unpredictable outcomes [31]. The use of genetic algorithms in this study reflects this perspective by simulating adaptive processes and optimizing model parameters based on evolving behavioral patterns. This approach is also supported by earlier research on artificial stock markets, where evolutionary models have been used to study the behavior of adaptive traders and market dynamics [23].

In addition, the findings of this study are particularly relevant in the context of emerging markets, where volatility, uncertainty, and behavioral factors play a more pronounced role. Research on capital market stability and predictability in developing economies has highlighted the challenges associated with forecasting under conditions of structural instability and limited information [9]. The present study addresses these challenges by incorporating behavioral variables into the predictive framework, thereby improving its applicability to volatile and uncertain market environments. This is especially important given the critical role of capital markets in financing economic growth and development [8].

Overall, the results of this study provide strong empirical support for the integration of behavioral finance and computational intelligence in market trend prediction. By demonstrating that investors' financial behavior is a powerful predictor of market trends and that genetic algorithms can significantly enhance predictive performance, this study offers a comprehensive and practical framework for financial forecasting. The findings also highlight the importance of considering psychological and behavioral factors in addition to traditional financial variables, particularly in volatile market conditions where uncertainty and emotional responses are heightened.

The limitations of this study should be acknowledged to provide a balanced interpretation of the findings. First, the study was conducted using cross-sectional data, which limits the ability to capture dynamic changes in investor behavior over time. Second, the sample was restricted to investors in the Tehran Stock Exchange, which may limit the generalizability of the findings to other markets with different institutional and economic characteristics. Third, although the study incorporated multiple behavioral dimensions, it did not include all possible psychological and macroeconomic variables that may influence market behavior. Fourth, the reliance on self-reported questionnaire data may introduce response bias, particularly in measuring subjective constructs such as risk-taking and emotional reactions. Finally, while the genetic algorithm improved model performance, its results depend on parameter settings and may vary under different configurations.

Future research can build on the findings of this study by addressing its limitations and exploring new directions. Longitudinal studies could be conducted to examine how investors' financial behavior evolves over time and how these changes affect market dynamics. Comparative studies across different countries and market structures could provide insights into the generalizability of the proposed model. Researchers could also incorporate additional variables, such as macroeconomic indicators, geopolitical risk, and technological factors, to enhance the comprehensiveness of the model. Furthermore, integrating other advanced machine learning techniques, such as deep learning and reinforcement learning, with evolutionary algorithms could further improve predictive accuracy. Finally, future studies could explore the role of real-time behavioral data, such as social media sentiment and trading activity logs, in enhancing market prediction models.

From a practical perspective, the findings of this study have important implications for capital market stakeholders. Policymakers can use the insights from this research to design regulations and interventions that mitigate the impact of behavioral biases on market stability. Portfolio managers can incorporate behavioral indicators into their investment strategies to improve decision-making and risk management. Investors can benefit from a better understanding of their own behavioral tendencies and how these tendencies influence their financial decisions. Additionally, financial institutions can develop more sophisticated forecasting tools that integrate behavioral data with computational intelligence methods. Overall, the integration of behavioral finance and advanced optimization techniques can provide a more effective framework for managing uncertainty and enhancing performance in capital markets.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

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

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

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