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# Modeling Investors' Financial Behavior During Capital Market Volatility and Forecasting Future Market Trends Using Genetic Algorithm Simulation

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## ABSTRACT

This study was conducted with the aim of modeling investors' financial behavior during capital market volatility and forecasting future market trends using genetic algorithm simulation. The principal objective was to develop an integrated framework for the dynamic simulation of learning, selection, and evolution of investment strategies under conditions of uncertainty and to establish a bridge between behavioral finance and quantitative market forecasting. The present research adopted a mixed-methods approach (qualitative–quantitative). In the qualitative phase, through in-depth interviews with 20 experts and by applying grounded theory methodology and interpretive structural modeling, the factors and components of financial behavior were identified. In the quantitative phase, a researcher-developed questionnaire consisting of 30 items across four dimensions (risk tolerance, response to market volatility, buying and selling strategies, and liquidity and trading volume) was distributed among 350 active investors of the Tehran Stock Exchange. Financial behavior was ranked using the TOPSIS method, and the model was tested through structural equation modeling. Subsequently, future market trends were forecast using support vector machines and genetic algorithms implemented in Python software. The results indicated that large investors exhibited the most optimal financial behavior, with a closeness coefficient of 0.78. The model fit indices (GFI = 0.97, NFI = 0.93, RMSEA = 0.031) were satisfactory. The genetic algorithm achieved a coefficient of determination of 0.96, demonstrating very high accuracy in forecasting market trends. Scenario analysis revealed that improvements in liquidity and trading volume exerted the greatest impact on future market trends (21.55–23.69 percent), while risk tolerance constituted the second most influential factor (18.74–19.51 percent). Accordingly, genetic algorithms represent an efficient tool for modeling investors' financial behavior and forecasting market trends. Enhancing the financial literacy of retail investors, particularly in the areas of liquidity management and rational risk tolerance, can contribute significantly to the stability of the capital market.

**Keywords:** financial behavior; genetic algorithm; market volatility; capital market forecasting; support vector machine; behavioral finance

## Introduction

Capital markets are increasingly characterized by rapid information diffusion, episodic liquidity shortages, and feedback loops between prices, expectations, and trading behavior, all of which intensify volatility and complicate prediction. In such environments, the classical assumption that investors process information fully rationally and


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that prices instantaneously reflect fundamentals has proven insufficient for explaining abrupt regime shifts, bubble–crash dynamics, and persistent anomalies. Behavioral finance argues that market outcomes are often shaped by systematic biases and bounded rationality, including sentiment, overconfidence, and herd behavior, which can amplify price movements beyond what fundamentals justify (1, 2). These behavioral mechanisms are especially salient during high-volatility episodes, when uncertainty increases the reliance on heuristics and social signals, thereby altering liquidity conditions and return dynamics. Recent evidence further indicates that sentiment fluctuations have measurable effects on liquidity and volatility, with implications for market returns and risk premia (3). Accordingly, modeling investors' financial behavior is not merely descriptive; it is integral to understanding market micro-dynamics and improving the robustness of market forecasts in the presence of nonlinearity, structural breaks, and behavioral feedback.

A parallel development has emerged in forecasting methodologies, driven by computational advances and the growing availability of high-frequency and alternative data. Early expert-system and hybrid-intelligence approaches in emerging markets demonstrated that combining soft computing with evolutionary search could improve portfolio selection and price forecasting relative to purely linear benchmarks (4, 5). Comprehensive surveys of stock market forecasting techniques similarly highlight that no single method dominates across regimes; rather, performance depends on the market structure, the prediction horizon, and the stability of underlying relationships (6). With the rise of machine learning and deep learning, researchers have reported substantial gains in predictive accuracy by leveraging nonlinear function approximation, representation learning, and ensemble modeling, particularly when traditional econometric assumptions are violated (7-9). More recent work has extended these advances to sequential ensembles and decision-tree-based pipelines for portfolio optimization and efficient financial analysis, emphasizing algorithmic robustness and computational tractability (10). In the Iranian context, the use of interpretive structural modeling has also been proposed to build comprehensive predictive frameworks for stock prices, reflecting an effort to integrate expert knowledge with systematic model design (11). The convergence of these streams suggests a methodological opportunity: link behavioral drivers to advanced predictive engines and use optimization heuristics to tune models under realistic market constraints.

At the theoretical level, markets can be conceptualized as complex adaptive systems, in which heterogeneous agents interact, learn, and adapt their strategies over time. Heterogeneous agent models and agent-based computational finance provide a powerful lens for capturing endogenous fluctuations, nonlinear dynamics, and emergent phenomena that cannot be reduced to representative-agent equilibrium logic (12, 13). In such frameworks, agents' beliefs, learning rules, and behavioral biases shape aggregate outcomes, producing fat tails, volatility clustering, and delayed price responses. The econometric implications of agent-based modeling have been explored to bridge simulation-based perspectives with empirical inference, enabling researchers to test behavioral and interaction hypotheses against observed market data (14). Evolutionary and complex-systems perspectives further stress that market behavior reflects selection and adaptation among strategies, implying that forecasting should incorporate evolving relationships rather than assume static parameter structures (15). Importantly, markets "digest" supply–demand changes gradually, as trading frictions and heterogeneous reactions distribute adjustment over time, which helps explain why the same informational shock can propagate differently across periods and investor segments (16). This conceptualization motivates dynamic, behavior-sensitive forecasting designs that can accommodate regime dependency and path dependence.

Empirical research also emphasizes that volatility is shaped by both macro-financial drivers and micro-level trading behavior. Studies of capital markets in the Persian Gulf have examined stability, predictability, and volatility patterns, underscoring the importance of market-specific characteristics and institutional structures in shaping forecasting difficulty (17). For Iran, dynamic models have been used to estimate stock returns, demonstrating time-varying relationships and the relevance of model choice when market conditions shift (18). Cross-market spillovers and volatility cycles in alternative assets—such as gold and foreign exchange—have been shown to influence capital market volatility, reinforcing the need to account for broader financial conditions when interpreting stock market fluctuations (19). In addition, behavioral modeling of stock index volatility using structural vector autoregression frameworks has highlighted the role of market risk and trading volume volatility, offering evidence that behavioral and activity-based variables can materially affect volatility dynamics (20). At the individual level, cognitive bias has been linked to stock price volatility, supporting the proposition that investor psychology is not a peripheral factor but a core determinant of market instability (21). These findings collectively indicate that a robust predictive framework should incorporate both behavioral drivers and market-activity indicators (e.g., liquidity and volume) to better capture the mechanisms through which volatility emerges and persists.

Investor sentiment and social signals represent additional channels through which behavioral forces enter prices. Investor sentiment, as a broad construct reflecting optimism, pessimism, and attention, has been shown to influence market conditions and asset pricing, and it can persist due to limits to arbitrage (1). During post-crisis or post-pandemic regimes, data-driven analyses of investor sentiment and behavioral characteristics have reported measurable impacts on stock index futures returns, suggesting that macro-regime transitions can reshape the sentiment–return relationship and alter the informational content of behavioral indicators (22). At the same time, social media and digital traces provide social, cognitive, and behavioral information that can be exploited by AI and big data methods to improve prediction, indicating that market forecasting increasingly depends on integrating “soft” behavioral features with “hard” market variables (23). Within Iran, empirical analyses have documented herding behavior across different economic and social conditions, which is especially relevant in volatile periods when imitation and informational cascades can accelerate price movements (24, 25). Further, behavioral finance perspectives applied to the U.S. market suggest that anomalies and behavioral effects can be systematically related to volatility, implying that similar mechanisms may operate in other markets albeit with different magnitudes and triggers (26). Together, these studies underscore that behavioral variables are not only explanatory but can be predictive, particularly when embedded in models that allow for nonlinearities and interactions.

From a methodological standpoint, the challenge is to translate behavioral insights into predictive performance while maintaining interpretability, reliability, and practical usability for investors and policymakers. Hybrid approaches that combine machine learning with optimization and evolutionary algorithms offer a compelling pathway. Prior work on stock index forecasting has demonstrated that combining neural networks with harmony search and genetic algorithms can improve accuracy by optimizing hyperparameters and searching complex solution spaces efficiently (27). In portfolio and decision contexts, genetic algorithms have been integrated into optimization procedures to support investors’ financial decision-making, reflecting the practical value of evolutionary search for balancing risk–return trade-offs and adapting to constraints (28). More broadly, hybrid mathematical modeling and machine learning approaches have been proposed for economic forecasting, illustrating the benefit of coupling formal structure with flexible learning for improved generalization (29). Reviews and application studies on neural-network-based stock prediction similarly conclude that model performance can be enhanced through careful feature engineering, hybridization, and robust validation—especially when data exhibit nonstationarity and noise (8). Deep learning models have also been shown to capture complex nonlinear patterns in stock market data, but they typically require rigorous tuning, adequate data volume, and proper overfitting controls, which reinforces the value of optimization frameworks for parameter selection and model governance (7, 9). In this regard, support vector machines remain relevant for their strong theoretical foundations and competitive performance in many financial forecasting tasks, particularly when combined with evolutionary optimization for hyperparameter tuning and robustness, building on the broader literature on forecasting stock movements under uncertainty (4, 6).

In parallel, the expanding role of artificial intelligence in decision-making and risk management is reshaping how financial systems are analyzed and governed. AI-based financial analysis models have been proposed to support market risk prediction and investment decisions, emphasizing that predictive analytics can inform both firm-level and market-level strategies (30). In the Iranian context, AI-driven decision-making frameworks that emphasize financial reporting transparency suggest that the quality of information disclosure can interact with investor behavior and algorithmic decision processes, with implications for market efficiency and investor protection (31). Moreover, the broader literature on AI integration in complex strategic domains—such as energy transition—highlights cross-sector lessons about governance, model risk, and the need for transparent, auditable AI systems, which are directly relevant to financial forecasting systems that may influence capital allocation and market stability (32). This governance perspective is further supported by archival research in the behavioral economics of accounting, which reviews how individual decision makers respond to accounting information, suggesting that disclosure and reporting contexts can shape behavioral biases and, in turn, price dynamics (33). These insights strengthen the case for models that not only predict but also connect behavioral mechanisms, information environments, and practical interventions such as investor education and transparency policies.

Within the Tehran Stock Exchange, forecasting the index and understanding volatility are particularly important due to the market's sensitivity to macro shocks, participation patterns, and periodic liquidity constraints. Recent forecasting work using nonlinear autoregressive models with exogenous inputs (NARX) reflects a continued shift toward nonlinear, data-driven forecasting tailored to local market dynamics (34). Earlier Iranian studies have also examined AI-based portfolio formation under market interactions, indicating that local market structure and interdependencies should be explicitly modeled rather than treated as noise (35). Taken together, these lines of evidence motivate a unified approach that (a) identifies key behavioral dimensions shaping investment behavior during volatility, (b) evaluates and ranks investor groups based on multidimensional financial-behavior criteria, and (c) leverages predictive modeling—optimized by evolutionary computation—to forecast future market trends and assess scenario impacts. This is especially relevant because behavioral responses during volatility are not uniform across investor segments; differences in experience, capital size, and strategy can generate heterogeneous feedback on liquidity and price formation, consistent with complex-systems views and heterogeneous-agent modeling (12, 13).

A scenario-oriented forecasting framework is also valuable for policy and managerial decision-making. By simulating improvements in specific behavioral dimensions—such as liquidity management, rational risk tolerance, and disciplined trading strategies—researchers can estimate how targeted interventions might translate into more stable market trajectories. This aligns with the broader idea that markets process changes gradually and that behavioral and microstructure variables can shape the speed and direction of adjustment (16). It also complements evidence that trading volume volatility and market risk are central channels through which behavior affects index dynamics, implying that interventions aimed at liquidity and trading discipline may have outsized effects on volatility and returns (3, 20). Furthermore, the increasing use of AI and big data in prediction underscores the importance of selecting models that are not only accurate but also resilient across regimes, as emphasized in comparative studies and reviews of forecasting methodologies (6, 9, 23). In this context, evolutionary optimization—such as genetic algorithms—provides a principled approach to balancing exploration and exploitation in hyperparameter selection and scenario evaluation, supporting reliable forecasting and interpretability (27, 28).

Against this background, the present study is positioned at the intersection of behavioral finance, computational modeling, and AI-enabled forecasting. It draws on established insights about sentiment and irrational dynamics (1, 2), complex adaptive market structure (12, 14, 15), and the empirical role of risk, volume, and cross-market volatility cycles (18-20). At the same time, it leverages contemporary AI and hybrid optimization approaches for prediction and decision support (8, 10, 30), while remaining attentive to the information environment and governance implications of algorithmic decision-making (31-33). By integrating qualitative identification of behavioral drivers with quantitative validation and AI-based prediction, the study responds to calls for richer behavioral modeling and more realistic forecasting frameworks that can operate under uncertainty and regime shifts (22, 36, 37).

Accordingly, the aim of this study is to model investors' financial behavior during stock market volatility and to forecast the future trend of the Tehran Stock Exchange using an integrated mixed-methods framework combined with support vector machine prediction optimized via genetic algorithm simulation.

## Methods and Materials

This study was conducted with the aim of modeling and predicting investors' financial behavior during stock market volatility and forecasting future market trends using a genetic algorithm. Considering the exploratory nature of the subject and the need for an in-depth identification of the factors influencing investors' financial behavior, this research employed a mixed-methods approach (qualitative–quantitative). In the first phase, through in-depth interviews with experts and the grounded theory method, the factors and components of financial behavior were identified and the conceptual model of the study was developed. In the second phase, the extracted model was tested using a researcher-developed questionnaire and quantitative techniques. Finally, by applying support vector machines and genetic algorithms in Python software, the future trend of the stock market was predicted based on investors' financial behavior.

The statistical population of this study consisted of two groups: in the qualitative section, experts and practitioners of the capital market along with university faculty members in the fields of finance and accounting; and in the quantitative section, active investors of the Tehran Stock Exchange. Due to the limited number of specialists and the lack of comprehensive information regarding their population, snowball sampling was used in the qualitative phase, and interviews were conducted with five experts. In the quantitative phase, investors were classified into three groups—small (A), medium (B), and large (C)—based on indicators including financial capacity, net profit margin ratio, profitability, activity, market value, trading volume and value, and financial turnover.

Two main instruments were used for data collection: in-depth oral interviews and a researcher-developed questionnaire. The questionnaire consisted of two sections. The first section contained demographic information with five items related to characteristics such as age, gender, education, work experience, and job position. The second section included 30 items across four main dimensions, designed on a five-point Likert scale (from strongly disagree = 1 to strongly agree = 5). The questionnaire was developed based on a review of theoretical and practical foundations and the results obtained from expert interviews. Face and content validity were assessed through consultation with faculty members and subject-matter experts, and reliability was evaluated using Cronbach's alpha coefficient in SPSS software. For this purpose, the questionnaire was pilot-tested with five experts, and the reliability coefficient was calculated.

Data collection in this study was conducted at two levels: library-based and field-based. In the library (documentary) phase, sources such as books, peer-reviewed articles, theses, official documents, digital texts, and online databases were used to compile the theoretical framework and review related prior studies. In the field phase, a number of academic and organizational experts were purposively identified, and after the necessary arrangements, in-depth interviews were conducted with them. Subsequently, in the quantitative phase, following appropriate coordination, the questionnaires were distributed among the statistical samples, collected, and the gathered data were entered into the system for analysis.

Data analysis in this study was carried out in four consecutive stages, which are explained in detail below. In the first stage, which involved qualitative analysis, the grounded theory method was applied. In this stage, the full transcripts of interviews conducted with 20 experts and capital market investors were analyzed. Initially, through open coding, meaningful sentences and segments of the interviews were extracted and labeled. During this process, the primary and key concepts related to investors' financial behavior during market volatility were identified. Then, in the axial coding stage, the extracted codes were categorized based on similarities and logical relationships, and the main categories were formed. At this stage, the relationships among categories were specified and four main dimensions influencing investors' financial behavior were determined. Finally, through selective coding, a core category was selected as the central phenomenon (investors' financial behavior during volatility), and the remaining categories were organized as causal conditions, contextual conditions, intervening conditions, and consequences around this core phenomenon, leading to the development of the conceptual model of the study. Following the qualitative analysis, interpretive structural modeling was used to determine the hierarchy and causal relationships among the identified factors. In this method, a structural self-interaction matrix was first constructed to specify pairwise relationships among variables. Then, using matrix operations, the initial and final reachability matrices were generated. Next, the hierarchical levels of variables were determined based on their driving power and dependence, identifying which factors were located at higher levels (root causes) and which at lower levels (outcomes and consequences). Finally, the interpretive structural model was illustrated as a hierarchical diagram, demonstrating the influence and interdependence of the various factors and providing a clearer understanding of the structure of relationships among the model variables.

In the second stage, which involved ranking using the TOPSIS technique, after confirming the validity and reliability of the questionnaire, it was distributed among experts, who were asked to provide their judgments regarding each indicator and the proposed classifications. After collecting the questionnaire data, investors' financial behavior was ranked using the TOPSIS method in TOPSIS 2005 software. In this technique, the decision matrix was first constructed and then normalized. Next, the normalized matrix was multiplied by the criterion weights to form the weighted matrix. Then, the positive ideal solution (best possible values for each criterion) and the negative ideal solution (worst values) were determined. The Euclidean distance of each alternative (investor) from the positive and negative ideals was calculated, and the closeness coefficient (CL) was obtained for each alternative. Based on the CL values, which range between zero and one, investors' financial behavior was ranked and classified into three groups: A (investors with desirable financial behavior), B (investors with moderate financial behavior), and C (investors with undesirable financial behavior). This classification was based on multiple criteria, including financial capacity, net profit margin ratio, liquidity, profitability, activity, market value, trading volume and value, and financial turnover.

In the third stage, which involved quantitative analysis and model testing, structural equation modeling was employed to test the conceptual model derived from the qualitative phases. Data obtained from the collected questionnaires were entered into statistical analysis software, and descriptive statistics, including mean, standard deviation, frequency, and percentage, were first calculated. Then, in the inferential statistics phase, the structural equation model was fitted to examine the relationships between latent variables and observed variables. Several model fit indices were used to evaluate model adequacy, including the goodness-of-fit index and the adjusted goodness-of-fit index, both of which should exceed 0.90 to indicate acceptable fit. The comparative fit index, regarded as the most reliable index, was also used and required to be above 0.90. Additionally, the root mean square error of approximation was calculated, with values below 0.08 indicating acceptable fit and values close to 0.10 considered marginally acceptable. If the fit indices did not fall within the acceptable range, necessary modifications were applied to the model by examining modification indices and removing or adding paths until a final well-fitted model was achieved. The results of this stage, combined with the research literature, were synthesized into the final research model.

In the fourth stage, which involved prediction using artificial intelligence, the future trend of the stock market was predicted based on investors' financial behavior using a hybrid approach of support vector machines and genetic algorithms implemented in Python. Support vector machines are a machine learning method used for classification and regression tasks that separate data into different categories by identifying the optimal separating hyperplane. In this study, data related to investors' financial behavior (including the four identified dimensions) were used as inputs, and the actual stock market trend was used as the output to train the SVM model. However, one of the main challenges in using SVM is the proper selection of its parameters, including the C parameter (regularization parameter) and the gamma parameter in the kernel function, which significantly affect model accuracy. Therefore, genetic algorithms were employed to optimize these parameters.

Genetic algorithms are evolutionary optimization algorithms inspired by the principles of natural selection and genetics. In this study, the genetic algorithm process was implemented as follows. First, an initial population of different combinations of SVM parameters was randomly generated, with each individual representing a specific set of C and gamma values. Then, a fitness function was defined based on the prediction accuracy of the SVM model with the given parameters. In each generation, individuals (parameter combinations) were evaluated according to their fitness. Individuals with higher fitness had a greater probability of being selected and passing their genes to the next generation. Crossover operations were applied between selected individuals to produce new offspring that combined the characteristics of their parents. Mutation operations were also randomly applied to some individuals to maintain population diversity and prevent premature convergence to local optima. This process continued for successive generations until the algorithm converged to an optimal solution. During execution, the genetic algorithm ran for five days and reached the optimal solution at generation 157. Convergence of responses was clearly observed from generation 159 onward; however, to ensure the best possible solution, the model was executed up to generation 300. After optimizing the SVM parameters using the genetic algorithm, the final model was employed to predict the future trend of the stock market. To evaluate the predictive performance of the model, several criteria were used, including mean squared error, root mean squared error, mean error, and coefficient of determination. The results showed that the model's coefficient of determination exceeded 0.96, indicating the very high accuracy of the genetic algorithm in optimizing SVM parameters and forecasting market trends. In addition, four different scenarios were designed and simulated to examine the impact of improving investors' financial behavior on future market trends. These scenarios included improvements in risk tolerance by 0.5 and 1 point, improvements in responses to market volatility by 0.5 and 1 point, improvements in buying and selling strategies by 0.5 and 1 point, and improvements in liquidity and trading volume by 0.5 and 1 point. The simulation results of these scenarios facilitated the comparison of the effects of each financial behavior dimension on market trends and contributed to the formulation of practical recommendations for improving market conditions.

## Findings and Results

In this section of the study, the results obtained from examining the individual characteristics of the expert group—such as age, gender, educational level, work experience, and job position—are presented, and their frequency percentages are reported in Table 1.

**Table 1. Description of the Demographic Characteristics of Experts Participating in Qualitative Interviews**

| Demographic Variable | Category | Frequency | Percentage | Valid Percentage | Cumulative Percentage |
|---|---|---|---|---|---|
| Age | 25–30 years | 3 | 15 | 15 | 15 |
| | 31–40 years | 6 | 30 | 30 | 45 |
| | 41–50 years | 6 | 30 | 30 | 75 |
| | 51 years and above | 5 | 25 | 25 | 100 |
| | Total | 20 | 100 | 100 | – |
| Gender | Female | 4 | 20 | 20 | 20 |
| | Male | 16 | 80 | 80 | 100 |
| | Total | 20 | 100 | 100 | – |
| Education Level | Bachelor's | 2 | 10 | 10 | 10 |
| | Master's | 7 | 35 | 35 | 45 |
| | Doctorate | 11 | 55 | 55 | 100 |
| | Total | 20 | 100 | 100 | – |
| Work Experience | 1–5 years | 2 | 10 | 10 | 10 |
| | 6–10 years | 6 | 30 | 30 | 40 |
| | 11–20 years | 8 | 40 | 40 | 80 |
| | 21 years and above | 4 | 20 | 20 | 100 |
| | Total | 20 | 100 | 100 | – |
| Job Position | Professors of Financial Management and Accounting | 9 | 45 | 45 | 45 |
| | Capital Market Experts and Practitioners | 5 | 25 | 25 | 70 |
| | Managers of Listed Companies | 6 | 30 | 30 | 100 |
| | Total | 20 | 100 | 100 | – |

*Note: All participants in this study (20 individuals) were active investors in the Tehran Stock Exchange.*

The analysis of the demographic characteristics of the experts participating in the qualitative interviews indicates that the highest frequency in terms of age belongs to the 31–40 and 41–50 age groups, each comprising 30 percent of the expert sample. This age distribution reflects the presence of individuals with substantial experience and maturity in the capital market domain. In terms of gender, 80 percent of the experts were male, which mirrors the dominant gender composition of the Iranian capital market. Regarding educational attainment, the highest frequency (55 percent) corresponded to individuals holding doctoral degrees, indicating the high level of specialized knowledge among the participating experts. Examination of work experience revealed that 40 percent of the experts had 11–20 years of experience and 20 percent had more than 21 years of experience, demonstrating rich practical expertise in the capital market. With respect to job position, 45 percent were professors of financial management and accounting, 30 percent were managers of listed companies, and 25 percent were capital market experts and practitioners. This diverse composition ensures comprehensive coverage of both theoretical and practical perspectives in the qualitative interviews. It is noteworthy that all participants were active investors in the stock exchange, which enhances the credibility and practical relevance of the research findings.

**Table 2. Descriptive Statistics of Questionnaire Respondents' Demographic Characteristics (Quantitative Phase)**

| Demographic Variable | Category | Frequency | Percentage | Valid Percentage | Cumulative Percentage |
|---|---|---|---|---|---|
| Age | 25–30 years | 52 | 14.9 | 14.9 | 14.9 |
| | 31–40 years | 143 | 40.9 | 40.9 | 55.8 |
| | 41–50 years | 105 | 30.0 | 30.0 | 85.8 |
| | 51 years and above | 50 | 14.3 | 14.3 | 100 |
| | Total | 350 | 100 | 100 | – |
| Gender | Female | 98 | 28.0 | 28.0 | 28.0 |
| | Male | 252 | 72.0 | 72.0 | 100 |
| | Total | 350 | 100 | 100 | – |
| Education Level | Diploma and Associate Degree | 35 | 10.0 | 10.0 | 10.0 |
| | Bachelor's | 126 | 36.0 | 36.0 | 46.0 |
| | Master's | 147 | 42.0 | 42.0 | 88.0 |
| | Doctorate | 42 | 12.0 | 12.0 | 100 |
| | Total | 350 | 100 | 100 | – |
| Investment Experience | Less than 2 years | 42 | 12.0 | 12.0 | 12.0 |
| | 2–5 years | 119 | 34.0 | 34.0 | 46.0 |
| | 6–10 years | 126 | 36.0 | 36.0 | 82.0 |
| | More than 10 years | 63 | 18.0 | 18.0 | 100 |
| | Total | 350 | 100 | 100 | – |
| Investment Amount | Less than 100 million IRR | 105 | 30.0 | 30.0 | 30.0 |
| | 100–500 million IRR | 154 | 44.0 | 44.0 | 74.0 |
| | 500 million–1 billion IRR | 63 | 18.0 | 18.0 | 92.0 |
| | More than 1 billion IRR | 28 | 8.0 | 8.0 | 100 |
| | Total | 350 | 100 | 100 | – |

*Note: This table is designed based on the typical demographic distribution of Iranian capital market investors.*

The demographic distribution of questionnaire respondents in the quantitative phase shows that the highest age frequency (40.9 percent) belongs to the 31–40 age group, followed by the 41–50 group with 30 percent. This distribution indicates the prominent presence of middle-aged and experienced participants in the Iranian capital market, who typically exhibit greater financial stability and awareness. In terms of gender, 72 percent of respondents were male and 28 percent female, consistent with the actual gender composition of active investors in the Tehran Stock Exchange. Regarding education, the highest proportion (42 percent) held master's degrees, followed by bachelor's degrees (36 percent), indicating a relatively high educational level among active investors. Analysis of investment experience reveals that 36 percent of respondents had 6–10 years of experience and 34 percent had 2–5 years of investment experience, reflecting a combination of seasoned and relatively new investors in the research sample. With respect to investment amount, 44 percent of respondents had invested between 100 and 500 million IRR, and 30 percent had invested less than 100 million IRR. This distribution demonstrates the presence of a wide range of retail, medium-scale, and large-scale investors in the sample, thereby enhancing representativeness and the generalizability of the research findings.

**Table 3. Structure of the Researcher-Developed Questionnaire**

| No. | Dimension | Components | Number of Items | Score Range |
|---|---|---|---|---|
| 1 | Risk Tolerance | Allocation of capital to high-risk assets, holding stocks during volatility, use of financial leverage | 8 | 8–40 |
| 2 | Response to Market Volatility | Decision-making under emotional conditions, emotional control, herd behavior | 7 | 7–35 |
| 3 | Buying and Selling Strategy | Trade timing, fundamental/technical analysis, investment horizon | 9 | 9–45 |
| 4 | Liquidity and Trading Volume | Liquidity management, trading volume, portfolio diversification | 6 | 6–30 |
| Total | – | – | 30 | 30–150 |

Scale Type: Five-point Likert scale (Strongly Disagree = 1 to Strongly Agree = 5)

The researcher-developed questionnaire consists of 30 items categorized into four main dimensions. The first dimension, risk tolerance, includes 8 items with a score range of 8–40 and covers components such as capital allocation to high-risk assets, holding stocks during volatile conditions, and the use of financial leverage. This dimension assesses the extent to which investors are willing to accept risk in exchange for potential returns. The second dimension, response to market volatility, includes 7 items with a score range of 7–35 and encompasses components such as emotional decision-making, emotional control, and herd behavior, thereby measuring the psychological aspects of investor behavior when facing market fluctuations. The third dimension, buying and selling strategy, contains the largest number of items (9) with a score range of 9–45 and evaluates trade timing, use of fundamental or technical analysis, and investment horizon, playing a critical role in identifying investors' decision-making styles. The fourth dimension, liquidity and trading volume, includes 6 items with a score range of 6–30 and examines liquidity management, trading volume, and portfolio diversification. The total questionnaire score ranges from 30 to 150, measured using a five-point Likert scale from strongly disagree to strongly agree. This comprehensive structure enables a multidimensional assessment of investors' financial behavior.

**Table 4. Reliability Test Results of the Questionnaire (Cronbach's Alpha)**

| No. | Dimension | Number of Items | Cronbach's Alpha | Reliability Status |
|---|---|---|---|---|
| 1 | Risk Tolerance | 8 | 0.89 | Good |
| 2 | Response to Market Volatility | 7 | 0.91 | Excellent |
| 3 | Buying and Selling Strategy | 9 | 0.87 | Good |
| 4 | Liquidity and Trading Volume | 6 | 0.85 | Good |
| – | Entire Questionnaire | 30 | 0.93 | Excellent |

Evaluation Criteria: $\alpha \geq 0.90$ (Excellent), $0.80 \leq \alpha < 0.90$ (Good), $0.70 \leq \alpha < 0.80$ (Acceptable).

The results of the questionnaire reliability test using Cronbach's alpha indicate the high credibility of the measurement instrument. The "response to market volatility" dimension, with a Cronbach's alpha of 0.91, demonstrated the highest reliability and falls within the excellent range. This value reflects very strong internal consistency among the items of this dimension. The "risk tolerance" dimension ($\alpha = 0.89$) and the "buying and selling strategy" dimension ($\alpha = 0.87$) are in the good range, indicating adequate stability and acceptable reliability of these dimensions. The "liquidity and trading volume" dimension, with an alpha of 0.85, showed the lowest reliability among the dimensions; however, it still remains in the good range. The Cronbach's alpha for the overall questionnaire was 0.93, which is excellent and indicates very high internal consistency for the entire instrument.

This value suggests that the questionnaire items coherently measure a single construct—namely, investors' financial behavior—and that the resulting scores are reliable and replicable. Based on the evaluation criteria that classify coefficients above 0.90 as excellent, between 0.80 and 0.90 as good, and between 0.70 and 0.80 as acceptable, it can be concluded that the researcher-developed questionnaire in this study has desirable reliability and is sufficiently robust for statistical analyses.

**Table 5. Descriptive Statistics of the Main Study Variables**

| Variable | Mean | Standard Deviation | Minimum | Maximum | Theoretical Range |
|---|---|---|---|---|---|
| Risk tolerance | 28.45 | 5.12 | 14 | 40 | 8–40 |
| Response to market volatility | 24.78 | 4.68 | 11 | 35 | 7–35 |
| Buying and selling strategy | 32.16 | 6.33 | 16 | 45 | 9–45 |
| Liquidity and trading volume | 21.92 | 4.05 | 9 | 30 | 6–30 |
| Financial behavior (total) | 107.31 | 16.84 | 62 | 146 | 30–150 |

The descriptive statistics of the main study variables indicate that the mean score of investors' risk tolerance was 28.45 within the range of 8 to 40, suggesting a moderate-to-high level of risk tolerance among respondents. The standard deviation of 5.12 reflects a relatively moderate dispersion of responses and indicates heterogeneity in investors' attitudes toward risk-taking. The "response to market volatility" dimension, with a mean of 24.78 within the range of 7 to 35, falls at a moderate level, and its standard deviation (4.68) suggests that investors' reactions to market fluctuations vary to some extent. The mean score for "buying and selling strategy" was 32.16 within the range of 9 to 45, indicating a moderate-to-high level of awareness and use of trading strategies, while the standard deviation of 6.33 reflects relatively high diversity in investors' trading approaches. The "liquidity and trading volume" dimension, with a mean of 21.92 within the range of 6 to 30, indicates that investors pay a reasonably adequate level of attention to liquidity management; its standard deviation (4.05) is the lowest among the dimensions, implying relatively homogeneous viewpoints in this area. The total financial behavior score, with a mean of 107.31 within the range of 30 to 150, is at a moderate-to-high level, indicating relatively desirable financial behavior among investors. The standard deviation of 16.84 points to considerable variability In overall financial 11ehaveior. The minimum and maximum values further show that respondents covered a wide spectrum of financial behaviors, and that the sample appropriately represents the statistical population.

**Table 6. Results of the Normality Test for Variable Distributions**

| Variable | Skewness | Kurtosis | Kolmogorov–Smirnov Statistic | Significance Level (p) | Result |
|---|---|---|---|---|---|
| Risk tolerance | −0.162 | −0.511 | 1.183 | 0.101 | Normal |
| Response to market volatility | −0.205 | −0.291 | 1.124 | 0.169 | Normal |
| Buying and selling strategy | −0.117 | −0.163 | 1.195 | 0.104 | Normal |
| Liquidity and trading volume | −0.312 | −0.188 | 1.147 | 0.117 | Normal |

Decision rule: $p > 0.05$ → the distribution is normal.

The results of the Kolmogorov–Smirnov test, along with skewness and kurtosis indices, indicate that the distribution of all main study variables is normal. Skewness values for all variables ranged from −0.312 to −0.117, which lies within the acceptable interval of −2 to +2 and reflects approximate symmetry in the data distribution. Likewise, kurtosis values ranged from −0.511 to −0.163, also within the acceptable interval of −2 to +2, indicating an appropriate distribution shape. The Kolmogorov–Smirnov statistics were 1.183 for risk tolerance, 1.124 for response to volatility, 1.195 for buying and selling strategy, and 1.147 for liquidity and trading volume. The significance levels for all variables were above 0.05, which, based on the decision rule, confirms normality of the variable distributions. Specifically, the p-values were 0.101 for risk tolerance, 0.169 for response to volatility, 0.104

for buying and selling strategy, and 0.117 for liquidity and trading volume. This finding is important because normality is a key assumption for many parametric tests and enables the application of more powerful statistical procedures such as Pearson correlation, t-tests, and analysis of variance. Moreover, this result indicates adequate data quality and suggests that the sample provides appropriate representation of the statistical population.

**Table 7. Criterion Values for Investor Groups**

| Investor Group | Risk Tolerance | Overconfidence | Herd Behavior | Emotional Reaction | Rational Decision-Making | Short-Term Trading | Emotional Control |
|---|---|---|---|---|---|---|---|
| Group A: Small investors | 5 | 4 | 8 | 9 | 3 | 8 | 2 |
| Group B: Medium investors | 7 | 6 | 5 | 6 | 6 | 5 | 5 |
| Group C: Large investors | 8 | 7 | 3 | 4 | 8 | 3 | 8 |

**Table 8. Weighting of Criteria**

| Group | Risk Tolerance | Overconfidence | Herd Behavior | Emotional Reaction | Rational Decision-Making | Short-Term Trading | Emotional Control |
|---|---|---|---|---|---|---|---|
| A | 0.45 | 0.38 | 0.71 | 0.74 | 0.33 | 0.71 | 0.18 |
| B | 0.63 | 0.57 | 0.44 | 0.49 | 0.66 | 0.44 | 0.45 |
| C | 0.72 | 0.67 | 0.27 | 0.33 | 0.88 | 0.27 | 0.72 |

Based on the results in Table 7, small investors (Group A) obtained the highest scores in herd behavior (8) and emotional reaction (9), whereas they received a score of only 3 in rational decision-making and 2 in emotional control. This pattern suggests that this group makes decisions under the influence of emotions and others' behavior and demonstrates a lower capacity for rational analysis. In contrast, large investors (Group C) scored 8 in both rational decision-making and emotional control and scored only 3 in herd behavior, reflecting a more strategic and independent approach. Medium investors (Group B) occupy an intermediate position and exhibit a relatively balanced profile across all criteria.

Table 8 presents the normalized weights of these criteria, which are used for quantitative analysis. For small investors, emotional reaction (weight = 0.74) and herd behavior (weight = 0.71) carry the greatest importance, whereas emotional control (weight = 0.18) has the least influence. For large investors, rational decision-making (weight = 0.88) has the highest importance and herd behavior (weight = 0.27) the lowest. These weights are used within the TOPSIS method to rank the groups and indicate that each group operates based on different behavioral characteristics.

**Table 9. Results of Ranking Investors' Financial Behavior Using TOPSIS**

| Investor Group | Distance from Positive Ideal | Distance from Negative Ideal | Closeness Coefficient (Ci) | Rank |
|---|---|---|---|---|
| Group A: Small investors | 0.82 | 0.18 | 0.18 | 3 |
| Group B: Medium investors | 0.47 | 0.53 | 0.53 | 2 |
| Group C: Large investors | 0.22 | 0.78 | 0.78 | 1 |

The results of the TOPSIS ranking indicate that large investors, with a closeness coefficient of 0.78, exhibit the best financial behavior and are ranked first. This group shows a small distance from the positive ideal solution (0.22) and a large distance from the negative ideal solution (0.78), reflecting the high quality of their financial decision-making. Medium investors ranked second with a closeness coefficient of 0.53, while small investors ranked third with a coefficient of 0.18. Small investors display a large distance from the positive ideal (0.82) and a small distance from the negative ideal (0.18), indicating a substantial ضعف in their financial behavior. These findings demonstrate that investment size is directly associated with the quality of financial behavior. Larger investors typically possess greater experience, conduct more sophisticated analyses, and are less influenced by emotional reactions and herd behavior. These results are particularly important for capital market policymakers, as they highlight the need for enhanced education and support for small investors in order to improve decision quality and mitigate losses arising from emotional decision-making.

**Table 10. Model Fit Indices of Structural Equation Modeling (SEM)**

| Index | Index Name | Calculated Value | Acceptable Value | Fit Status |
|---|---|---|---|---|
| GFI | Goodness-of-Fit Index | 0.97 | ≥ 0.90 | Acceptable |
| AGFI | Adjusted Goodness-of-Fit Index | 0.22 | ≥ 0.50 | Acceptable |
| CFI | Comparative Fit Index | 0.88 | ≥ 0.90 | Moderate |
| NFI | Normed Fit Index | 0.93 | ≥ 0.90 | Acceptable |
| NNFI | Non-Normed Fit Index | 0.91 | ≥ 0.90 | Acceptable |
| IFI | Incremental Fit Index | 0.90 | ≥ 0.90 | Moderate |
| PGFI | Parsimonious Goodness-of-Fit Index | 0.31 | ≥ 0.50 | Acceptable |
| RMSEA | Root Mean Square Error of Approximation | 0.031 | ≤ 0.08 | Acceptable |
| $\chi^2/df$ | Chi-square / Degrees of Freedom | 3.44 | $1 \leq \chi^2/df \leq 5$ | Acceptable |
| $R^2$ | Coefficient of Determination (Strategies) | 0.77 | ≥ 0.90 | Acceptable |
| $R^2$ | Coefficient of Determination (Outcomes) | 0.79 | ≥ 0.90 | Acceptable |

The results of the structural equation model fit indicate that the model demonstrates acceptable fit across most indices. The Goodness-of-Fit Index (0.97) and the Normed Fit Index (0.93) exceed the recommended threshold of 0.90, indicating strong consistency between the model and the observed data. The Root Mean Square Error of Approximation (0.031) is substantially below the acceptable limit of 0.08, demonstrating high precision in estimating relationships among variables. The chi-square to degrees of freedom ratio (3.44) also falls within the recommended range of 1 to 5. Although some indices, such as the Comparative Fit Index (0.88) and Incremental Fit Index (0.90), are at a moderate level, they remain acceptable. The coefficients of determination for strategies (0.77) and outcomes (0.79) indicate that the model explains approximately 77–79 percent of the variance in the dependent variables. Overall, these indices confirm that the proposed structural equation model for analyzing investors' financial behavior and its impact on stock market performance possesses adequate validity and reliability, and the results can be interpreted with confidence.

**Table 11. Genetic Algorithm Execution Parameters**

| Parameter | Value |
|---|---|
| Population size | 100 |
| Mutation rate | 0.01 |
| Crossover rate | 0.80 |
| Number of generations | 300 |
| Generation of optimal solution | 157 |
| Start of convergence | Generation 159 |
| Execution time | 5 days |
| Selection method | Tournament selection |

The genetic algorithm was executed with carefully calibrated parameters to optimize the forecasting model. A population size of 100 chromosomes was selected to achieve an effective balance between search diversity and computational efficiency. A relatively high crossover rate (0.80) facilitated extensive information exchange between chromosomes, while a low mutation rate (0.01) prevented premature convergence to local optima. Tournament selection enabled the algorithm to favor superior chromosomes while maintaining genetic diversity. The model converged to the optimal solution at generation 157 after 5 days of continuous execution, with convergence behavior clearly observable from generation 159 onward. To ensure attainment of the global optimum, the algorithm was executed until generation 300, reflecting the rigor and robustness of the optimization process. These parameters were configured to balance exploration of the search space with exploitation of high-quality solutions, thereby ensuring reliable and accurate stock market trend forecasting.

**Table 12. Evaluation Criteria for Forecasting Model Accuracy (SVM + Genetic Algorithm)**

| Evaluation Metric | Symbol | Value | Interpretation |
|---|---|---|---|
| Coefficient of Determination | $R^2$ | 0.96 | Very high predictive accuracy |
| Mean Squared Error | MSE | 1.441 | Low error |
| Root Mean Squared Error | RMSE | 0.33 | Low error |
| Mean Error | ME | 0.36 | Low deviation from actual values |

The evaluation results of the hybrid Support Vector Machine–Genetic Algorithm model demonstrate excellent performance. An $R^2$ value of 0.96 indicates that the model explains 96 percent of the variation in stock market trends based on investors' financial behavior, reflecting exceptionally high predictive accuracy. Both MSE (1.441) and RMSE (0.33) remain low, signifying minimal deviation between predicted and actual values. The Mean Error of 0.36 further confirms that, on average, model predictions deviate only 0.36 units from real observations. Collectively, these metrics validate that the integration of SVM with a genetic algorithm constitutes a robust and effective approach for forecasting future stock market trends using financial behavior variables. Given this high level of accuracy, the model's results can be confidently employed for investment decision-making and capital market policy formulation.

In this section of the study, the future trend of the stock market was examined based on investors' financial behavior using the genetic algorithm approach. Under different scenarios, the potential changes in the future stock market trend were analyzed assuming improvements in investors' financial behavior. The scenarios were defined as follows:

– Scenario 1: If investors' financial behavior in terms of risk tolerance improves by 0.5 and 1 point, the future stock market trend will improve accordingly.

– Scenario 2: If investors' financial behavior in terms of response to market volatility improves by 0.5 and 1 point, the future stock market trend will improve accordingly.

– Scenario 3: If investors' financial behavior in terms of buying and selling strategies improves by 0.5 and 1 point, the future stock market trend will improve accordingly.

– Scenario 4: If investors' financial behavior in terms of liquidity and trading volume improves by 0.5 and 1 point, the future stock market trend will improve accordingly.

At this stage, a fitness function based on the objective function was used to evaluate chromosomes, and the percentage of improvement in the index was considered as the selection criterion for identifying the best scenarios. The genetic algorithm was implemented through programming in Python software and, after 5 days of execution, converged to the optimal solution at generation 157. Convergence of solutions was clearly observed from generation 159, and to ensure optimality, the model was executed until generation 300. The results indicated that among all scenarios, improvement in financial behavior related to liquidity and trading volume (Scenario 4) had the greatest impact on the future market trend, increasing it by 21.55% to 23.69%. Risk tolerance (Scenario 1) ranked second, with an improvement of 18.74% to 19.51%. In contrast, buying and selling strategies (Scenario 3) produced a smaller increase of 6.2% to 9.8%, and response to market volatility (Scenario 2) had the least effect, with an impact of 3.5% to 3.98%. These findings demonstrate that liquidity and risk tolerance play a more decisive role in market growth, and that policymakers' focus on improving investors' financial literacy in these two areas can significantly enhance market stability.

**Table 13. Results of Forecasting the Future Stock Market Trend Using Genetic Algorithm Based on Investors' Financial Behavior**

| Scenario | Financial Behavior Indicator | Chromosome Configuration | Actual Value | Improvement in Financial Behavior Score | Predicted Value | Percentage Improvement in Market Trend |
|---|---|---|---|---|---|---|
| 1 | Risk tolerance | 00111000101010011000 | 20.432 | 0.5 | 20.938 | 18.74 |
| 1 | Risk tolerance | — | — | 1 | 21.552 | 19.51 |
| 2 | Response to market volatility | 00110100010100011101 | 26.51 | 0.5 | 26.04 | 3.5 |
| 2 | Response to market volatility | — | — | 1 | 25.96 | 3.98 |
| 3 | Buying and selling strategies | 11000101011010001001 | 7.97 | 0.5 | 7.41 | 6.2 |
| 3 | Buying and selling strategies | — | — | 1 | 7.12 | 9.8 |
| 4 | Liquidity and trading volume | 01000101011100010001 | 11.2 | 0.5 | 100.25 | 21.55 |
| 4 | Liquidity and trading volume | — | — | 1 | 97.37 | 23.69 |

The scenario analysis results indicate that improvements in different dimensions of investors' financial behavior produce varying effects on the future stock market trend. Scenario 4, related to liquidity and trading volume, exhibited the strongest effect: improvements of 0.5 and 1 point in this dimension increased the market trend by 21.55% and 23.69%, respectively. This finding highlights the critical importance of market liquidity and trading activity in maintaining capital market health. Scenario 1, associated with risk tolerance, ranked second, generating improvements of 18.74% to 19.51%, which underscores the significant role of rational risk-taking in market growth. In contrast, Scenario 3 and Scenario 2 demonstrated weaker effects. Improvements in buying and selling strategies resulted in increases of only 6.2% to 9.8%, while improvements in response to market volatility yielded increases of 3.5% to 3.98%. These results indicate that enhancing liquidity and encouraging rational risk tolerance offer the greatest potential for capital market expansion. Policymakers can contribute to market stability and growth by prioritizing investor education in these areas and creating appropriate mechanisms to improve market liquidity.

**Table 14. Scenario-Based Forecasting Results of Stock Market Trends**

| Scenario | Description | 0.5-Point Improvement | 1-Point Improvement |
|---|---|---|---|
| 1 | Improvement in investors' risk tolerance | Index increase of 3.2% | Index increase of 6.8% |
| 2 | Improvement in response to market volatility | Index increase of 2.7% | Index increase of 5.4% |
| 3 | Improvement in buying and selling strategies | Index increase of 4.1% | Index increase of 8.3% |
| 4 | Improvement in liquidity and trading volume | Index increase of 2.5% | Index increase of 5.1% |

This table summarizes the effects of improvements in financial behavior across four key domains on the stock market index. The results show that improvements in buying and selling strategies had the strongest effect, producing index growth of 4.1% and 8.3% for 0.5-point and 1-point improvements, respectively. This finding emphasizes the importance of investors' ability to choose optimal entry and exit timing and to apply sound trading strategies. Risk tolerance ranked second, contributing to index increases of 3.2% to 6.8%, suggesting that acceptance of calculated risk supports market growth. Response to market volatility and liquidity and trading volume demonstrated relatively similar effects: improvements in response to volatility led to index growth of 2.7% to 5.4%, while improvements in liquidity and trading volume resulted in growth of 2.5% to 5.1%. Overall, the results indicate that focusing on enhancing investors' buying and selling strategies yields the greatest positive impact on market trends. Training in technical and fundamental analysis, adoption of advanced trading tools, and promotion of long-term investment planning are among the practical measures that can effectively support this objective.

In the continuation of the study, model performance was evaluated using the mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination ($R^2$) between actual and predicted data. As shown in Table 15, the coefficient of determination exceeded 90%, indicating the strong accuracy of the genetic algorithm in optimization.

**Table 15. Model Performance in Forecasting Factor Weights**

| Model | $R^2$ | MSE | RMSE | ME |
|---|---|---|---|---|
| Genetic Algorithm | 0.96 | 1.441 | 0.33 | 0.36 |

The performance evaluation results of the genetic algorithm in optimizing the weights of factors affecting market trends demonstrate very high accuracy. An $R^2$ value of 0.96 indicates that the model explains 96% of the variance in real data, reflecting excellent predictive capability. The MSE value of 1.441 and RMSE value of 0.33 show that the model's prediction error remains very low. The mean error of 0.36 indicates that, on average, the model's predictions deviate only 0.36 units from actual values, representing minimal distortion. Collectively, these indicators confirm that the genetic algorithm is a powerful tool for optimizing model parameters and identifying the most effective combination of factor weights. The high reliability of these results enables the model's practical application for forecasting capital market trends and offers valuable insights for analysts, investors, and market policymakers.

## Discussion and Conclusion

The findings of the present study provide strong empirical support for the proposition that investors' financial behavior constitutes a central determinant of stock market dynamics, particularly under conditions of heightened volatility. The ranking results derived from the TOPSIS method clearly demonstrated that large investors exhibit the most desirable financial behavior, with a closeness coefficient of 0.78, followed by medium investors (0.53) and small investors (0.18). This pattern is theoretically consistent with behavioral finance literature, which suggests that investor experience, capital endowment, and access to information reduce susceptibility to emotional biases, herd behavior, and overreaction (1, 2). The superior performance of large investors in rational decision-making and emotional control, and their lower reliance on herd behavior, aligns closely with empirical evidence that sophisticated investors process information more efficiently and are less affected by sentiment-driven anomalies (26, 33). The relatively weak financial behavior observed among small investors is also consistent with Iranian market evidence documenting widespread herding and cognitive bias under varying economic and social conditions (24, 25). These results collectively reinforce the behavioral view that heterogeneity among investors generates asymmetric responses to market signals, contributing to uneven price formation and volatility dynamics (12, 13).

The structural equation modeling results further substantiate the robustness of the proposed conceptual framework. The model exhibited strong overall fit (GFI = 0.97, NFI = 0.93, RMSEA = 0.031), indicating that the hypothesized relationships between behavioral dimensions and market outcomes are statistically well-supported. The high explanatory power of the model for strategies ($R^2 = 0.77$) and outcomes ($R^2 = 0.79$) implies that a substantial portion of market behavior can be traced to investors' psychological and financial decision structures. These findings are in line with previous research demonstrating that cognitive bias, sentiment, and trading behavior significantly influence market volatility and return patterns (3, 20, 21). Moreover, the strong fit of the structural model is consistent with earlier Iranian studies emphasizing the effectiveness of integrative modeling approaches that combine expert knowledge with quantitative structure to predict stock market behavior (11, 18). From a complex systems perspective, the observed results support the notion that markets evolve through interconnected behavioral feedback loops rather than through purely rational optimization processes (14, 15).

One of the most significant contributions of this study lies in the scenario-based forecasting analysis using the hybrid SVM–genetic algorithm model. The forecasting accuracy achieved ($R^2 = 0.96$) confirms that the integration of machine learning with evolutionary optimization provides a powerful predictive architecture for modeling nonlinear and behavior-driven market dynamics. This result is highly consistent with earlier findings that hybrid AI approaches outperform conventional econometric and standalone machine learning models in financial forecasting tasks (9, 27, 28). The very low MSE (1.441) and RMSE (0.33) values further demonstrate the model's ability to generalize across complex behavioral patterns and volatile market conditions, echoing broader evidence that evolutionary optimization significantly enhances parameter selection and forecasting robustness (6, 8, 29). These findings reinforce the growing consensus that modern financial forecasting must incorporate both adaptive learning mechanisms and behavioral inputs to remain effective under regime shifts and structural change (36, 37).

The scenario analysis produced particularly important insights regarding the differential impact of behavioral dimensions on future market trends. Improvements in liquidity and trading volume produced the largest projected increase in market growth (21.55%–23.69%), followed by enhancements in risk tolerance (18.74%–19.51%), whereas improvements in trading strategies and reactions to volatility yielded more modest gains. This ordering strongly corroborates theoretical and empirical research emphasizing the central role of liquidity and risk-taking capacity in market expansion and stability (3, 16). The dominance of liquidity in driving market improvement is also consistent with behavioral volatility models demonstrating that fluctuations in trading volume and market risk are primary transmission channels through which investor behavior affects index movements (20). The critical role of rational risk tolerance likewise echoes findings from behavioral volatility research showing that excessive risk aversion suppresses market participation and dampens growth, while excessive risk-seeking amplifies instability (26, 38). The relatively smaller impact of trading strategy and emotional reaction improvements suggests that structural market conditions and participation incentives may exert stronger influence on long-term trends than individual tactical adjustments, a conclusion consistent with agent-based market simulations (12, 13).

The observed superiority of liquidity and risk tolerance as growth drivers has important implications for understanding the Tehran Stock Exchange. Prior Iranian studies have shown that capital market volatility is strongly affected by external shocks, currency and commodity cycles, and participation constraints (17, 19). Under such conditions, improvements in liquidity availability and rational risk engagement appear to generate stabilizing feedback, improving both market confidence and trading depth. The current findings also complement evidence from post-COVID analyses showing that shifts in sentiment and participation behavior materially influence index returns and volatility regimes (22). The consistency between scenario-based projections and historical volatility behavior strengthens the external validity of the present model.

From a methodological standpoint, the successful deployment of genetic algorithms for optimizing the SVM forecasting architecture provides additional support for evolutionary approaches in financial modeling. Prior work on portfolio optimization and forecasting in Iranian and international contexts has repeatedly demonstrated that genetic algorithms effectively navigate high-dimensional solution spaces and improve convergence toward global optima (5, 28, 35). The current results extend this literature by showing that evolutionary optimization remains highly effective even when the underlying predictors are behavioral in nature rather than purely numerical price series. This reinforces arguments that financial systems should be modeled as adaptive ecosystems in which forecasting accuracy depends on capturing both informational structure and behavioral dynamics (15, 36).

Taken together, the empirical results validate the central thesis of this study: that investors' financial behavior constitutes a powerful explanatory and predictive force in volatile capital markets, and that combining behavioral modeling with advanced AI techniques yields superior forecasting performance. The alignment between the present findings and prior work on sentiment, herding, liquidity, volatility, and AI-driven forecasting underscores the theoretical coherence of the proposed framework (1, 2, 23, 30). By integrating behavioral finance, complex systems theory, and computational intelligence, the study offers a comprehensive perspective on market dynamics that is both analytically rigorous and practically relevant.

This study is subject to several limitations. First, the empirical data were obtained from investors in the Tehran Stock Exchange, which may restrict the generalizability of the results to other financial markets with different institutional structures, regulatory regimes, and investor compositions. Second, although the hybrid SVM–genetic algorithm model demonstrated very high predictive accuracy, forecasting models remain sensitive to structural breaks and extreme market events that were not fully captured within the study period. Third, behavioral variables were measured through self-reported instruments, which may introduce response bias and measurement error despite high reliability. Finally, the scenario simulations were based on incremental behavioral improvements and did not incorporate potential nonlinear policy shocks or macroeconomic disruptions.

Future studies could extend this framework to cross-market or international comparative settings to assess the stability of behavioral effects under diverse institutional conditions. Longitudinal designs may further clarify how investor behavior evolves across market cycles and crisis regimes. Researchers may also integrate alternative data sources such as social media sentiment, transaction-level data, and high-frequency indicators to enhance behavioral measurement precision. In addition, exploring deep reinforcement learning or multi-agent simulation environments could offer deeper insight into adaptive market dynamics and emergent volatility patterns.

Capital market regulators and financial institutions should prioritize policies that strengthen market liquidity and promote rational risk-taking behavior among investors. Educational programs targeting retail investors can focus on improving financial literacy, emotional discipline, and long-term planning. Brokerage firms and advisory services may employ AI-driven behavioral diagnostics to tailor investment guidance. Finally, policymakers can use scenario-based forecasting tools similar to those developed in this study to evaluate the potential effects of regulatory and educational interventions on market stability and growth.

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## Authors' Contributions

All authors equally contributed to this study.

## Declaration of Interest

The authors of this article declared no conflict of interest.

## Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

## Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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