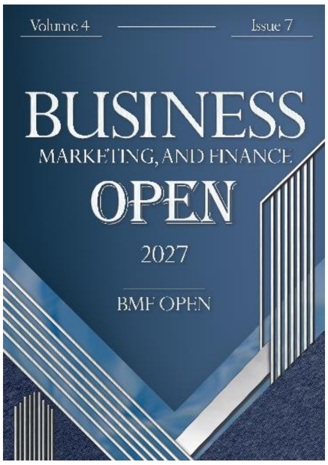
Predicting Corporate Financial Performance Using an Adaptive Neuro-Fuzzy Inference System Algorithm

Saeid Hooshmand [1], Morteza Bavaghar [2,*] , Hamid Rostamijaaz [3], Mohammad Hossein Ranjbar [4] and Hossein Kamrani [5]



Citation: Hooshmand, S., Bavaghar, M., Rostamijaaz, H., Ranjbar, M. H., & Kamrani, H. (2027). Predicting Corporate Financial Performance Using an Adaptive Neuro-Fuzzy Inference System Algorithm. *Business, Marketing, and Finance Open*, 4(7), 1-20.

Received: 10 May 2026
Revised: 21 August 2026
Accepted: 28 August 2026
Initial Publication: 29 August 2026
Final Publication: 01 December 2027

[1] Department of Accounting, BA.C., Islamic Azad University, Bandar Abbas, Iran;
[2] Department of Accounting, BA.C., Islamic Azad University, Bandar Abbas, Iran;
[3] Department of Accounting, BA.C., Islamic Azad University, Bandar Abbas, Iran;
[4] Department of Accounting and Finance, BA.C., Islamic Azad University, Bandar Abbas, Iran;
[5] Department of Accounting, BA.C., Islamic Azad University, Bandar Abbas, Iran;

* Correspondence: bavagharmorteza@iau.ac.ir

Abstract: The present study aimed to predict financial performance using an Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm. The study was conducted using an exploratory mixed-methods approach (qualitative–quantitative). In the qualitative phase, the fuzzy Delphi technique was employed with the participation of 10 academic and executive experts in the capital market to identify, prioritize, and screen variables affecting financial performance from a large pool of potential indicators. In the quantitative phase, data from 160 companies listed on the Tehran Stock Exchange over the 2016–2024 period (1,440 firm-year observations) were extracted and analyzed using ANFIS to predict "stock price return." The validity of the final model was assessed through two approaches: quantitatively, by evaluating its generalization accuracy using 421 test observations, and qualitatively, through expert judgment using a validation questionnaire. The fuzzy Delphi results led to the identification of 19 key variables in four categories: financial (7 indicators), economic (6 indicators), social (3 indicators), and macro-environmental (3 indicators). Furthermore, evaluation of the ANFIS model indicated that it explained 75.8% of the variance in stock price return. A comparison of actual and predicted values for 15 selected companies also confirmed that the model successfully tracked the overall trend in returns, although prediction errors increased slightly at extreme values. Accordingly, ANFIS demonstrated satisfactory and practically useful accuracy in predicting financial performance.

Keywords: financial performance prediction, stock return, artificial intelligence, Adaptive Neuro-Fuzzy Inference System, Tehran Stock Exchange

1. Introduction

Financial performance is one of the most fundamental criteria for evaluating organizational success, managerial effectiveness, competitive position, and the sustainability of firms in dynamic business environments. It reflects the extent to which an organization can efficiently employ its resources, generate profits, preserve liquidity, control financial risk, create value for shareholders, and maintain its capacity for growth over time. From the perspective of corporate management, financial performance is not merely the final outcome of accounting processes; rather, it represents the cumulative effects of strategic decisions, operational capabilities, economic conditions, human resources, institutional structures, and environmental uncertainties. Consequently, accurate assessment and prediction of financial performance have become central concerns for managers, investors, creditors, policymakers, and other stakeholders who must make decisions under conditions of uncertainty. In increasingly volatile capital markets, historical financial statements alone may be insufficient for anticipating future performance, particularly when firms are simultaneously exposed to economic shocks, technological disruption, institutional risk, and rapidly changing competitive conditions [1-3].

Traditional approaches to financial performance evaluation have generally relied on accounting ratios, financial statement analysis, conventional statistical models, and linear econometric techniques. Indicators such as profitability, liquidity, leverage, asset turnover, earnings growth, price-to-earnings ratios, and stock returns have long been used to evaluate corporate conditions and support investment decisions. These measures remain important because they provide interpretable information concerning operational efficiency, solvency, market expectations, and shareholder value. However, financial outcomes are rarely generated through simple linear relationships. The interaction between firm-specific variables and macroeconomic, social, political, and institutional conditions can produce complex, nonlinear, and time-varying patterns. Research on investment and stock selection has demonstrated the importance of risk-sensitive financial measures in portfolio construction, while studies of long-term stock returns have similarly emphasized that expected returns depend on complex processes that cannot always be adequately represented through conventional parametric assumptions [4, 5]. These limitations have increased interest in computational approaches capable of learning hidden relationships from large and multidimensional datasets.

The prediction of corporate financial performance becomes even more important in emerging capital markets, where macroeconomic instability, inflation, interest-rate changes, exchange-rate fluctuations, political risk, regulatory uncertainty, and market inefficiencies can intensify the volatility of corporate outcomes. In such settings, corporate financial performance cannot be understood solely through internal accounting information. Micro- and macro-level economic policy variables may influence financing costs, investment decisions, demand conditions, operating expenses, asset values, and profitability, thereby affecting both realized financial performance and stock-market valuation [1]. In the Iranian context, these challenges are particularly relevant because firms listed on the Tehran Stock Exchange operate in an economic environment characterized by considerable fluctuations in inflation, liquidity growth, interest rates, economic growth, and institutional conditions. Therefore, models intended to predict financial performance in this context should incorporate multidimensional explanatory variables rather than relying exclusively on traditional financial ratios.

In addition to financial and macroeconomic determinants, contemporary research increasingly highlights the role of intangible, organizational, and digital capabilities in explaining firm performance. Intellectual capital, technological adoption, knowledge resources, organizational adaptability, and digital transformation have become increasingly important sources of competitive advantage. Evidence indicates that intellectual capital and digital transformation can significantly contribute to firms' financial performance by strengthening innovation capacity, improving resource utilization, and enhancing organizational responsiveness [3]. Similarly, dynamic managerial capabilities and digital innovation have been associated with perceived financial performance, emphasizing the role of managerial competencies in sensing environmental changes, seizing opportunities, and reconfiguring organizational resources [2]. These developments indicate that the determinants of financial performance are expanding beyond conventional balance-sheet and income-statement measures, requiring predictive frameworks capable of integrating heterogeneous information.

Artificial intelligence has consequently emerged as an important analytical paradigm in financial and managerial decision-making. Unlike conventional statistical techniques that often depend on predefined assumptions regarding functional form, normality, independence, or linearity, artificial intelligence methods can identify nonlinear patterns and interactions directly from data. Artificial neural networks, machine-learning algorithms, fuzzy systems, deep-learning models, and hybrid intelligent systems are increasingly applied to classification, forecasting, risk assessment, profitability prediction, bankruptcy prediction, and investment analysis. The growing application of artificial intelligence across organizational functions also reflects a broader transformation in managerial systems. For example, artificial intelligence has been incorporated into human resource management frameworks to improve decision-making, automation, analytical capability, and organizational effectiveness [6]. At the organizational level, successful digital transformation depends on interacting individual, technological, organizational, and environmental factors, suggesting that the effectiveness of intelligent technologies is shaped by broader managerial and institutional contexts [7].

The relevance of artificial intelligence to financial performance is further supported by recent empirical research showing that AI-related innovation can directly influence corporate outcomes. Artificial intelligence innovation may improve decision quality, production efficiency, cost management, demand forecasting, and strategic responsiveness, thereby enhancing firm performance [8]. Moreover, comparative evidence indicates that advanced neural-network-based models may outperform conventional statistical techniques such as logistic regression in predicting corporate profitability, particularly when relationships among explanatory variables are nonlinear and complex [9]. These findings underscore an important methodological transition in financial management research: predictive accuracy increasingly depends on models capable of processing nonlinearities, interactions, uncertainty, and high-dimensional information.

Machine-learning techniques have also demonstrated considerable utility in the prediction of corporate distress and bankruptcy. Bankruptcy prediction is closely related to financial performance forecasting because both tasks require identification of patterns in financial indicators that precede future corporate outcomes. Machine-learning models have been shown to provide strong classification performance in bankruptcy prediction by learning complex relationships among financial variables and identifying combinations of indicators that conventional approaches may overlook [10]. Likewise, earlier work on bankruptcy discriminant models highlighted the sensitivity of conventional prediction models to specification and data characteristics, demonstrating the need for more robust approaches when financial relationships are unstable or heterogeneous [11]. In the Tehran Stock Exchange, gradient boosting algorithms have also been applied to predict financial performance and corporate distress, indicating the growing relevance of ensemble machine-learning methods in the Iranian financial context [12]. Together, these studies support the use of intelligent prediction techniques but also reveal the need to investigate alternative hybrid models that can combine learning capability with interpretable rule-based reasoning.

Among these hybrid approaches, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has attracted attention because it combines the computational learning capacity of artificial neural networks with the linguistic and reasoning capabilities of fuzzy inference systems. Neural networks are effective at identifying complex nonlinear mappings between inputs and outputs, but their internal structures are frequently criticized for being difficult to interpret. Fuzzy inference systems, in contrast, are well suited for representing ambiguous, imprecise, and expert-based knowledge through membership functions and fuzzy rules, yet conventional fuzzy systems may depend heavily on subjective specification. ANFIS integrates these two approaches by using neural-learning procedures to adjust the parameters of a fuzzy inference system. This architecture allows the model to learn from empirical observations while preserving a structured rule-based representation, making it especially appropriate for financial environments characterized by uncertainty, nonlinear relationships, and imprecise information.

Previous studies have demonstrated the potential of ANFIS in various financial prediction tasks. Arora and Saini applied an adaptive neuro-fuzzy inference system to bankruptcy prediction within a time-series framework and showed that hybrid neuro-fuzzy models could be used to model the temporal dynamics associated with corporate failure [13]. Choensawat and Polsiri similarly employed ANFIS for predicting financial institution failure using evidence from the East Asian economic crisis, illustrating its usefulness under highly unstable financial conditions [14]. These findings are relevant to financial performance prediction because they demonstrate that ANFIS can process multidimensional financial indicators and model nonlinear patterns under uncertainty. In addition, applications of adaptive filtering techniques to financial and monetary analysis have emphasized the importance of dynamically adjusting model parameters when the underlying data-generating process changes over time [15]. Such adaptability is particularly important for stock-market prediction, where relationships among explanatory variables can shift rapidly.

Neural and neuro-fuzzy systems have also been applied directly to stock-return prediction. Different neural-network architectures have been used to estimate stock-market returns, demonstrating that computational intelligence methods can identify patterns that may not be captured adequately by traditional forecasting approaches [16]. In Iran, a combination of wavelet decomposition and an adaptive neuro-fuzzy network has been used to predict Tehran Stock Market returns, highlighting the potential of ANFIS-based approaches for modeling nonlinear and nonstationary market data [17]. Similarly, applications of neural fuzzy systems and neural networks to the prediction of annual corporate returns suggest that hybrid systems can produce useful forecasting results when firm-level financial data contain complex interactions [18]. Collectively, these studies provide a methodological foundation for employing ANFIS in the prediction of corporate financial performance, particularly when stock price return is used as a market-based indicator of performance.

The quality of financial prediction, however, depends not only on the algorithm but also on the selection of appropriate input variables. Including irrelevant or redundant predictors can reduce model efficiency, increase computational complexity, and contribute to overfitting. Conversely, omitting important financial or contextual variables can weaken predictive validity. Therefore, a systematic variable-selection process is necessary before intelligent modeling. In management and financial research, expert-based techniques such as fuzzy Delphi and fuzzy multi-criteria decision methods provide useful mechanisms for evaluating the importance of variables when theoretical evidence is heterogeneous or context-dependent. Research applying fuzzy DEMATEL to financial performance has demonstrated that expert judgment can be used to identify and structure micro- and macro-level determinants of firm outcomes [1]. Integrating such qualitative screening with artificial intelligence can provide a stronger methodological foundation than relying exclusively on either literature-based variable selection or purely data-driven feature selection.

This issue is particularly important because financial performance is embedded within broader social, institutional, and informational environments. Human capital, labor-market conditions, governance quality, political risk, country risk, and corruption can influence managerial decision-making, investment confidence, financing conditions, productivity, and market expectations. The increasing emphasis on transparency also illustrates how information environments can affect stakeholder responses and organizational outcomes. Research on organizational and financial transparency has shown that greater transparency can influence stakeholder willingness to provide resources by functioning as a signal of performance or financial credibility [19]. Moreover, analyses of digital and social information increasingly employ advanced computational methods to extract patterns from complex data, demonstrating how artificial intelligence can support managerial interpretation and decision-making even in domains traditionally considered qualitative [20]. Thus, a comprehensive financial performance prediction model should recognize that firms operate within interconnected financial, economic, social, and macro-environmental systems.

Artificial neural networks have also demonstrated applicability beyond finance in predicting complex managerial and operational outcomes, reinforcing their general usefulness for nonlinear forecasting. Neural-network models have been employed in construction project prediction, where numerous interacting factors must be analyzed simultaneously to estimate future outcomes [21]. The relevance of such applications lies in the underlying analytical challenge: both project outcomes and financial performance emerge from combinations of measurable and partially uncertain factors whose relationships may not conform to linear assumptions. Consequently, adaptive computational models provide a flexible approach to modeling multidimensional managerial phenomena.

Despite substantial progress in artificial intelligence-based financial prediction, several research gaps remain. First, many studies emphasize either financial ratios or selected macroeconomic factors without systematically integrating financial, economic, social, and macro-environmental variables into a unified prediction framework. Second, a considerable proportion of previous research applies predefined variables without an explicit expert-based screening process adapted to the institutional and economic characteristics of the target market. Third, although machine-learning and deep-learning models may achieve high predictive performance, they often provide limited interpretability, whereas hybrid neuro-fuzzy models can combine data-driven learning with fuzzy rule structures. Fourth, relatively few studies in the Iranian capital market have integrated a qualitative expert-consensus phase with a quantitative ANFIS prediction phase. The combination of fuzzy Delphi screening and ANFIS modeling can address these limitations by first identifying contextually relevant variables and then estimating their nonlinear collective relationship with financial performance.

The prediction of stock price return also has practical significance because stock return represents an important market-based manifestation of financial performance and investor expectations. Accurate return prediction can assist investors in portfolio allocation, support managers in evaluating the market consequences of corporate decisions, and improve the ability of analysts to identify firms with favorable or unfavorable prospective conditions. Research on optimal portfolio selection in the Iranian stock market emphasizes the importance of risk-adjusted investment decision-making [4], while studies of long-term stock-return forecasting demonstrate continued demand for improved predictive models in financial management [5]. In this regard, the ability of ANFIS to learn nonlinear patterns while incorporating uncertainty may offer a meaningful advantage for predicting stock returns in an emerging market characterized by pronounced economic and institutional fluctuations.

Moreover, the development of a valid prediction model requires attention to both statistical generalizability and substantive validity. High performance on training data does not necessarily indicate that a model will provide reliable predictions for unseen observations. Model evaluation should therefore include independent test data and appropriate performance criteria such as the coefficient of determination, root mean square error, mean absolute error, and mean absolute percentage error. At the same time, expert assessment can provide complementary evidence regarding whether the structure, variables, logic, and practical applicability of a model are credible from a managerial perspective. Such combined validation is particularly useful for interdisciplinary models integrating financial management, artificial intelligence, and expert judgment. The increasing use of intelligent systems in organizational decision-making further strengthens the need for models that are not only technically accurate but also understandable and practically acceptable to decision-makers [6, 7].

Accordingly, the present study responds to the need for an integrated framework capable of identifying and predicting financial performance through both contextual expert knowledge and artificial intelligence. By combining the fuzzy Delphi method with ANFIS, the proposed approach enables the systematic identification and screening of relevant determinants before their incorporation into a nonlinear predictive model. This design is particularly suitable for the Tehran Stock Exchange, where company-specific financial indicators interact with inflation, interest rates, monetary conditions, labor-market characteristics, political risk, country risk, and institutional conditions. The resulting model can therefore provide both theoretical and practical value by expanding the conceptualization of financial performance beyond conventional ratios and demonstrating the predictive capability of hybrid intelligent systems in an emerging capital-market environment.

Therefore, the aim of the present study was to predict the financial performance of companies listed on the Tehran Stock Exchange, operationalized through stock price return, by identifying key financial, economic, social, and macro-environmental determinants using the fuzzy Delphi method and modeling their predictive relationships through an Adaptive Neuro-Fuzzy Inference System.

2. Methodology

The present study is applied in terms of purpose and falls within the category of descriptive-survey research with correlational and causal approaches in terms of its nature and implementation method. The data required for this study were collected through two methods: library-based research (secondary financial data) and field research (expert opinions). Accordingly, from the perspective of the research implementation process, a mixed-methods approach with a sequential exploratory design was adopted. In this design, the qualitative phase first draws on the research literature and expert opinions to identify and screen key financial performance indicators; subsequently, in the quantitative phase, mathematical approaches and intelligent algorithms are applied to confirm relationships and predict financial performance. In terms of the time dimension, the study is classified as cross-sectional in the qualitative phase and panel-data-based in the quantitative phase.

The statistical population of the qualitative phase consisted of academic experts (faculty members specializing in finance and management) and operational experts (senior financial managers of companies listed on the Tehran Stock Exchange). Non-probability purposive sampling was used to select members of the expert panel. The criterion for determining the sample size in this phase was the attainment of theoretical saturation. Although the identification of new indicators ceased after the tenth interview, indicating that saturation had been achieved, the interview process was continued with up to 13 participants in late summer 2025 to provide greater assurance and strengthen the reliability of the findings. The descriptive characteristics of the expert panel participating in the qualitative phase are presented in Table 1.

Table 1. Descriptive Statistics of the Demographic Characteristics of Participants (Interviewees) in the Qualitative Phase (Target Group: 10 Experts)

Demographic Characteristic	Category	Frequency	Highest Frequency	Lowest Frequency
Age	Below 35 years	3	35–45 years	Above 45 years
	35–45 years	5		
	Above 45 years	2		
Relevant work experience (professional/teaching experience)	Less than 7 years	4	7–14 years	More than 14 years
	7–14 years	4		
	More than 14 years	2		

Gender	Male	8	Male	Female
	Female	2		
Type of expert (theoretical or practical)	Theoretical	3	Practical	Theoretical
	Practical	7		
Field of study	Financial Management	6	Financial Management	Public Administration
	Public Administration	4		

Based on the analysis of the demographic data presented above, the following results were obtained. Three participants were university faculty members, including two assistant professors and one associate professor, while seven were operational experts. Of the participants, eight were men and two were women. Regarding academic specialization, four interviewees had backgrounds in management and six in finance. Four participants had less than 7 years of experience, four had between 7 and 14 years, and two had more than 14 years of work experience. In terms of age, three participants were younger than 35 years, five were between 35 and 45 years, and two were older than 45 years. These results indicate demographic diversity within the sample and its relevance to analyses of the research topic.

The statistical population of the quantitative phase also comprised all companies listed on the Tehran Stock Exchange during the 2016–2024 period. To select the statistical sample, systematic screening was conducted according to the following criteria:

- The company must have been admitted to the Tehran Stock Exchange before 2011, thereby having at least 15 years of continuous listing history by 2025.
- The financial data and financial statements required for the study during the 2016–2024 period must have been fully available in the CODAL system, and the company must not have experienced prolonged trading suspensions.
- The company must not have belonged to the financial intermediation, banking, insurance, or investment sectors because of the distinctive structure of their balance sheets and income statements.

After applying the above criteria, 160 companies were selected as the final research sample. Their financial statement data were obtained through library-based data collection using Rahavard Novin software and the CODAL system.

To contextualize and screen the financial performance indicators extracted from the theoretical literature, the fuzzy Delphi method was employed. In this process, a semi-open-ended questionnaire containing the preliminary indicators was provided to the expert panel. The experts assessed the importance of each indicator on a fuzzy scale using trapezoidal fuzzy numbers ranging from 0 to 10. Experts' revisions and suggestions were incorporated, and following the fuzzy Delphi rounds, the final indicators agreed upon by the panel were used as the basis for model development. After finalizing the input indicators in the first step and extracting companies' financial data in the second step, financial performance prediction was performed using an Adaptive Neuro-Fuzzy Inference System. Algorithm implementation, network training, and model testing were carried out in the MATLAB environment to obtain an optimized model with the minimum prediction error for forecasting companies' financial structure.

3. Findings and Results

As noted above, the fuzzy Delphi process was used in the present study to identify the relevant components. Initially, to construct the Delphi questionnaire, the components were identified through a review of the literature and structured interviews with experts. In the first step of identifying the components affecting "financial performance," a systematic and structured review of scientific sources was conducted. This systematic review resulted in the identification of a set of potential variables affecting financial performance that had been repeatedly discussed in the previous literature. Examples of the identified variables are presented below.

Table 2. Components Affecting Financial Performance Extracted Through the Literature Review

Influencing Factors	Scholars
Financial variables	Hosseini et al. (2018), Zarei et al. (2021), Johnson and Morris (2021), Martinez and Garcia (2024)
Economic variables	Taylor and White (2022), Martinez and Garcia (2024), Akbari et al. (2024), Roberts et al. (2022)
Social and environmental variables	Chen and Yu (2020), Chan (2020), Gorsen et al. (2024), Leung et al. (2023)

This set constituted the "preliminary list" of variables and was subsequently subjected to completion, revision, and refinement by experts in finance, accounting, data mining, and artificial intelligence. Although a literature review constitutes a credible source for identifying theoretical components, it may not fully reflect practical experiences and the specific conditions of Iran's economic environment. Therefore, in the second step, semi-structured interviews were conducted with experts. The interviews were recorded, transcribed, and analyzed using content analysis. Meaning units were extracted and categorized into initial codes. These codes were subsequently organized into concepts and thematic categories. The resulting components are presented in the following table.

Table 3. Components Affecting Financial Performance Extracted Through Expert Interviews

Influencing Factors	Indicators	Interviewee Codes
Financial variables	Profitability	I1, I3, I2, I8, I6
	Liquidity	I2, I10, I9
	Debt ratio	I8, I5, I6
	Asset turnover	I9, I1, I5, I6
	Earnings per share	I5, I6, I3, I4, I7
	Net income growth	I3, I7, I6
	Price-to-earnings ratio	I10, I9, I3, I7, I5
	Price volatility	I6, I8
Economic variables	Inflation rate	I6, I7
	Interest rate	I7, I9
	Monetary base and liquidity	I6, I10
	Unemployment rate	I7, I5
	Global oil price	I8, I4
	Consumer Price Index	I8, I3
	Gross domestic product growth	I5, I9
Social variables	Human Development Index	I10
	Level of economic freedom	I1, I3
	Good governance	I9, I2
	Human capital	I4, I3, I2
	Economically active population	I4, I1
	Labor force participation rate	I3, I10
Macro-environmental variables	Political risk	I5
	Country risk	I6
	Corruption	I10, I7
	Policy volatility	I2, I8
	Environmental sustainability	I1, I9

Following the preliminary identification of a set of financial, economic, environmental, and social variables through the systematic literature review and semi-structured expert interviews, the extracted list was incorporated into a fuzzy Delphi questionnaire and provided to the members of the expert panel. The purpose of implementing the fuzzy Delphi method was to establish consensus among experts and screen the indicators according to their importance, influence, and applicability in the financial performance prediction model. Initially, the questionnaires were distributed among the panel members. Through the fuzzy Delphi process and agreement on the evaluation criteria, 19 components were ultimately selected as the most important factors affecting financial performance. The final indicators identified as the most influential determinants of financial performance following completion of the fuzzy Delphi process and achievement of expert consensus are presented in the following table. These indicators formed the basis for entry into the predictive modeling stage using ANFIS.

Table 4. Final Approved Indicators Affecting Financial Performance: Fuzzy Delphi Results

Factor Category	Indicator	Final Defuzzified Score
Financial variables	Profitability	7.65
Financial variables	Liquidity	7.30
Financial variables	Debt ratio	7.65
Financial variables	Asset turnover	6.25
Financial variables	Net income growth	7.65
Financial variables	Price-to-earnings ratio	7.30
Financial variables	Price volatility	7.30
Economic variables	Inflation rate	7.17
Economic variables	Interest rate	5.55
Economic variables	Monetary base and liquidity	7.65
Economic variables	Unemployment rate	6.20
Economic variables	Consumer Price Index	7.65
Economic variables	Gross domestic product growth	7.65
Social variables	Human capital	7.30
Social variables	Economically active population	7.30
Social variables	Labor force participation rate	6.25
Macro-environmental variables	Political risk	7.65
Macro-environmental variables	Country risk	6.78
Macro-environmental variables	Corruption	7.65

Based on a threshold of 6.2, corresponding to two-thirds of the fuzzy scale interval (1.5–8.5), a total of 19 indicators across four categories were accepted as the principal inputs to the financial performance prediction models. These included financial indicators (profitability, liquidity, debt ratio, asset turnover, net income growth, price-to-earnings ratio, and price volatility), economic indicators (inflation rate, interest rate, monetary base and liquidity, unemployment rate, Consumer Price Index, and gross domestic product growth), social indicators (human capital, economically active population, and labor force participation rate), and macro-environmental indicators (political risk, country risk, and corruption). This set indicates that, in addition to conventional financial ratios, the experts considered macroeconomic variables, human capital, and political-institutional risks to be highly influential in predicting financial performance.

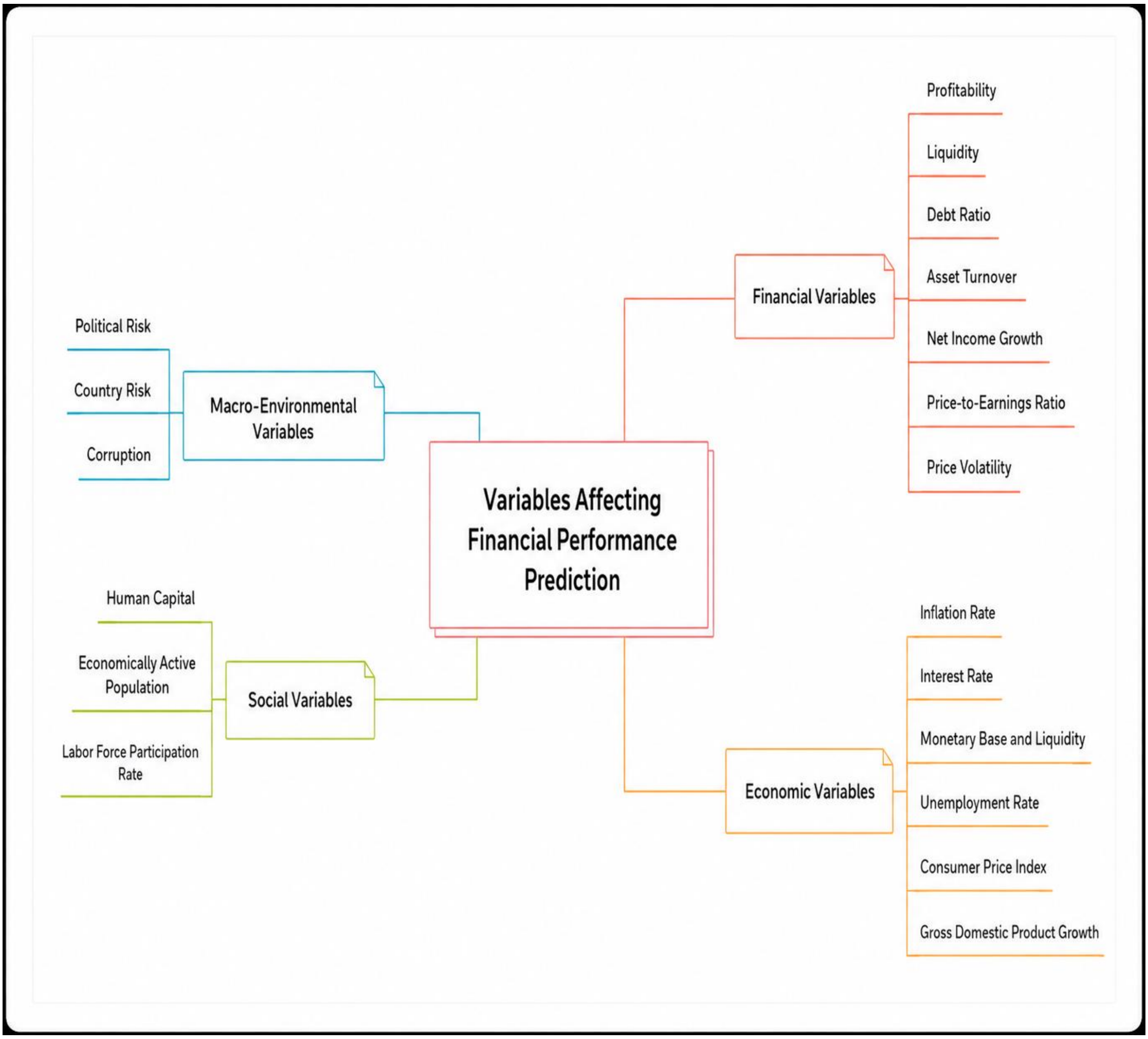


Figure 1. Variables Affecting Financial Performance Prediction

Following the identification of 19 indicators affecting financial performance through the fuzzy Delphi method in the qualitative phase, quantitative data relating to these indicators were collected for 160 companies listed on the Tehran Stock Exchange over the 2016–2024 period. The dependent (target) variable was stock price return, which was considered a quantitative measure of financial performance, and the powerful ANFIS algorithm was implemented and evaluated in MATLAB.

After applying the screening criteria, including continuous listing on the stock exchange, non-membership in the banking and investment industries, and availability of complete data, 160 companies over nine fiscal years generated a total of 1,440 initial firm-year observations. The distribution of companies by industry is presented in Table 5. As shown, the highest frequencies belonged to the petroleum and chemical products industry (28 companies), basic metals (22 companies), and food and beverages (20 companies), reflecting the principal structure of the Iranian capital market.

Table 5. Industry Distribution of the Sample Companies

No.	Industry	Number of Companies	Percentage
1	Petroleum and chemical products	28	17.5
2	Basic metals	22	13.8
3	Automotive and parts	18	11.3
4	Cement, gypsum, and lime	16	10.0
5	Pharmaceutical materials and products	14	8.8
6	Food and beverages	20	12.5
7	Non-metallic minerals	12	7.5
8	Machinery and equipment	10	6.3
9	Other industries	20	12.5
Total		160	100

The mean age of the companies was 23.4 years, and the mean book value of assets was IRR 8,740 billion, indicating that the sample comprised relatively large and well-established companies.

Table 6 presents the descriptive statistics for all research variables, including the 19 input variables and the output variable, based on 1,440 raw observations prior to any preprocessing.

Table 6. Descriptive Statistics of the Research Variables (Initial Number of Observations = 1,440)

Variable	Symbol	Unit	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
Output: Stock price return	Y	%	24.8	32.1	-45.6	215.3	1.82	7.14
Financial variables								
Profitability	X1	Ratio	0.09	0.11	-0.18	0.52	1.10	2.40
Liquidity (current ratio)	X2	Ratio	1.42	0.73	0.41	5.89	2.34	8.12
Debt ratio (total debt/assets)	X3	Ratio	0.63	0.18	0.10	0.98	-0.58	-0.20
Asset turnover (sales/assets)	X4	Ratio	0.72	0.34	0.12	2.10	1.02	1.58
Net income growth (relative to previous year)	X5	%	15.4	38.2	-82.0	310.5	2.75	16.3
Price-to-earnings ratio	X6	Ratio	6.85	5.40	1.20	38.7	2.88	11.8
Price volatility (monthly standard deviation)	X7	%	8.25	4.70	1.80	28.4	1.40	2.52
Economic variables								
Inflation rate (annual)	X8	%	31.5	10.2	9.6	46.5	-0.48	-0.65
Interest rate (one-year deposit rate)	X9	%	18.2	4.1	10.0	22.5	-0.62	-0.40
Monetary base and liquidity (annual growth)	X10	%	28.4	8.7	12.3	42.1	-0.25	-0.96
Unemployment rate	X11	%	10.8	1.9	8.1	14.2	0.11	-1.22
Consumer Price Index	X12	Index	210.5	65.3	118	340.2	0.72	-0.48
Gross domestic product growth	X13	%	1.8	3.5	-7.2	8.4	-0.38	0.40
Social variables								
Human capital (composite index)	X14	Score (0–1)	0.58	0.15	0.32	0.89	0.22	-0.72
Economically active population (proportion of total population)	X15	%	48.2	2.1	44.5	51.6	-0.15	-1.05
Labor force participation rate	X16	%	42.5	2.8	38.1	47.0	-0.20	-0.96
Macro-environmental variables								
Political risk	X17	Score (0–100)	48.3	8.5	32	62	-0.18	-0.75
Country risk (composite index)	X18	Score (0–100)	44.2	7.8	28	58	-0.10	-0.68
Corruption (control of corruption index)	X19	Score (0–100)	28.5	6.2	18	40	-0.06	-0.95

As indicated by the skewness and kurtosis values, variables such as stock return, net income growth, and the P/E ratio exhibit highly asymmetric distributions with heavy tails. This characteristic confirms the necessity of normalizing the data before their inclusion in artificial intelligence models.

To construct the initial fuzzy inference system, the subtractive clustering method was employed with an influence radius of 0.5, a squash factor of 1.25, an acceptance ratio of 0.5, and a rejection ratio of 0.15. This process generated 17 first-order Sugeno fuzzy rules with Gaussian membership functions. The network was trained over 200 epochs using the hybrid learning algorithm, which combines the least-squares method and gradient descent. The final root mean square error (RMSE) on the training data reached 0.0573 on the normalized scale.

The final parameters of the Adaptive Neuro-Fuzzy Inference System were as follows:

- Number of inputs: 19 variables (after normalization)
- Number of fuzzy rules: 17
- Membership function type: Gaussian
- Training method: Hybrid

The performance of the model on 421 observations in the test set (unseen data) is reported in Table 7.

Table 7. Performance of the Adaptive Neuro-Fuzzy Inference System on the Test Data

Criterion	Value (Original Scale)
Coefficient of determination (R^2)	0.758
Root mean square error (RMSE)	11.4%
Mean absolute error (MAE)	8.4%
Mean absolute percentage error (MAPE)	24.1%

To provide a direct illustration of the model's predictive accuracy, Table 8 presents the actual and predicted stock returns for 15 selected companies from the test set. This table serves as an alternative to a scatterplot and enables a more precise evaluation of the model's predictive performance.

Table 8. Actual and Predicted Stock Returns Using the Adaptive Neuro-Fuzzy Inference System: A Sample of 15 Companies From the Test Set

Company	Actual Return (%)	Predicted Return (%)	Absolute Error (%)
1	18.5	21.3	2.8
2	42.1	36.8	5.3
3	-12.7	-9.2	3.5
4	67.3	59.1	8.2
5	5.8	8.4	2.6
6	31.2	28.7	2.5
7	-15.0	-12.1	2.9
8	22.6	19.5	3.1
9	53.9	47.2	6.7
10	8.4	10.9	2.5
11	29.7	33.4	3.7
12	-4.1	-1.8	2.3
13	46.8	40.5	6.3
14	19.0	17.2	1.8
15	72.4	66.1	6.3
Mean	26.4	24.7	3.9

As shown in Table 8 and by the performance criteria reported in Table 7, the ANFIS model successfully tracked the overall trend in stock returns. However, in cases involving extreme returns, whether exceptionally high or low, prediction errors increased slightly, as observed for Companies 4, 9, 13, and 15. This phenomenon is common in machine-learning algorithms and can be attributed to the lower frequency of extreme observations in the training dataset.

In this study, the validity of the final model was assessed using a researcher-developed questionnaire adapted from Shoghi and Karimi (2025). The questionnaire comprised two sections: internal validity (10 items) and external validity (24 items), totaling 34 items. The questionnaire was administered to the same 10 experts who participated in the fuzzy Delphi panel, using a five-point Likert scale ranging from 1 (very low) to 5 (very high). After data collection, a one-sample *t* test with a test value of 3, representing the midpoint of the scale, was conducted using SPSS version 23. The component-level results are presented in the following tables.

Table 9. Descriptive Statistics and One-Sample t-Test Results for the Internal Validity of the Model

Component (Internal Validity)	Number of Items	Mean	SD	*t*	*df*	*p*	Result
Logical review	3	4.23	0.51	7.62	9	< .001	Significant
Expert feedback	4	4.10	0.48	7.25	9	< .001	Significant
Sensitivity analysis	3	4.07	0.56	6.04	9	< .001	Significant
Overall internal validity	10	4.13	0.42	8.48	9	< .001	Confirmed

Table 10. Descriptive Statistics and One-Sample t-Test Results for the External Validity of the Model

Component (External Validity)	Number of Items	Mean	SD	*t*	*df*	*p*	Result
Objective	4	4.35	0.47	9.08	9	< .001	Significant
Research method design	4	4.18	0.44	8.50	9	< .001	Significant
Control of confounding variables	8	4.01	0.38	8.39	9	< .001	Significant
Correspondence	7	4.09	0.41	8.36	9	< .001	Significant
Overall external validity	24	4.11	0.35	10.04	9	< .001	Confirmed

As the results indicate, the mean scores for all dimensions of internal validity (4.13) and external validity (4.11) were significantly higher than the test value of 3 ($p < .001$). These findings indicate that, according to the experts, the developed prediction model possesses acceptable logical coherence (internal validity), generalizability, and practical applicability (external validity). Accordingly, the qualitative validity of the model was also confirmed.

The mean internal validity score of the model was 4.13 out of 5 (SD = 0.42), which was significantly higher than 3 ($p < .001$). Among its components, “logical review” had the highest mean score (M = 4.23), whereas “sensitivity analysis” received the lowest score (M = 4.07); nevertheless, all components were evaluated at a very high level. The mean external validity score was 4.11 out of 5 (SD = 0.35), which was also significantly higher than 3 ($p < .001$). The “objective” component obtained the highest mean score (M = 4.35), while “control of confounding variables” obtained the lowest mean score (M = 4.01), which nevertheless remained substantially above the midpoint of the scale.

The significance levels of all tests ($p < .001$) indicate that the experts strongly endorsed the logical coherence (internal validity), generalizability, and practical applicability (external validity) of the model.

Overall, based on the quantitative evidence, including the relatively high coefficient of determination, prediction error below 20%, and absence of overfitting, as well as the experts’ qualitative confirmation, reflected in mean scores above 4 across all dimensions and statistically significant results, the financial performance prediction model developed using the Adaptive Neuro-Fuzzy Inference System demonstrated acceptable internal and external validity. The model can therefore be used as a reliable tool for predicting stock returns in the Iranian capital market.

The results of the Adaptive Neuro-Fuzzy Inference System based on 421 observations in the test set indicate that the model explained 75.8% of the variance in stock price return (R^2 = .758). The mean absolute prediction error was 8.4%, while the mean absolute percentage error was 24.1%. Furthermore, comparison of the actual and predicted values for 15 selected companies confirmed that the model was successful in tracking the overall trend in returns, although prediction error increased slightly at extreme values. Accordingly, ANFIS is capable of predicting financial performance with satisfactory and practically useful accuracy.

4. Discussion and Conclusion

The present study was conducted to predict the financial performance of companies listed on the Tehran Stock Exchange using an Adaptive Neuro-Fuzzy Inference System (ANFIS), after identifying and screening the most influential determinants through the fuzzy Delphi method. The findings of the qualitative phase showed that 19 indicators were ultimately confirmed as the most important predictors of financial performance. These indicators were classified into four groups: financial variables, including profitability, liquidity, debt ratio, asset turnover, net income growth, price-to-earnings ratio, and price volatility; economic variables, including inflation rate, interest rate, monetary base and liquidity, unemployment rate, Consumer Price Index, and gross domestic product growth; social variables, including human capital, economically active population, and labor force participation rate; and macro-environmental variables, including political risk, country risk, and corruption. In the quantitative phase, the ANFIS model demonstrated satisfactory predictive performance on 421 unseen test observations, explaining 75.8% of the variance in stock price return (R^2 = .758), with a root mean square error of 11.4%, a mean absolute error of 8.4%, and a mean absolute percentage error of 24.1%. Comparison of actual and predicted returns for selected companies further showed that the model closely followed the overall direction of stock returns, although prediction errors increased somewhat for extreme positive or negative observations. Taken together, these findings indicate that financial performance in the Tehran Stock Exchange can be predicted with practically meaningful accuracy through a hybrid intelligent model incorporating firm-level, macroeconomic, social, and institutional information.

One of the most important findings of the study was that financial performance could not be adequately conceptualized through conventional accounting and financial variables alone. Although financial indicators formed the largest category of accepted predictors, the fuzzy Delphi process also identified economic, social, and macro-environmental variables as essential inputs to the prediction model. This result is consistent with the view that corporate financial outcomes are shaped by an interaction between internal organizational conditions and external environmental forces. Previous research has shown that micro- and macro-level economic policy factors can influence firms' financial performance through financing costs, demand conditions, investment decisions, operating risks, and changes in asset values [1]. Similarly, contemporary research increasingly indicates that intellectual capital, organizational knowledge, and digital transformation contribute significantly to financial performance by enhancing efficiency, adaptability, and innovation capacity [3]. The inclusion of human capital and labor-market variables in the present model is therefore theoretically defensible because organizational performance depends not only on capital structure and profitability but also on the quality, availability, and productivity of human resources.

The identification of profitability, liquidity, leverage, asset turnover, net income growth, price-to-earnings ratio, and price volatility as important financial determinants is also consistent with the broader financial management literature. These indicators collectively reflect operating efficiency, solvency, financing structure, earnings dynamics, market valuation, and uncertainty. A firm with stronger profitability and asset utilization is generally more capable of generating returns from available resources, while liquidity and leverage capture its short-term resilience and long-term financial risk. The importance of stock-market measures is equally understandable because investors continuously incorporate expectations about future profitability and risk into securities prices. Prior studies in the Iranian capital market have shown that return prediction and portfolio optimization require simultaneous attention to both expected return and risk [4]. Likewise, research on long-term stock-return prediction has highlighted the need for more flexible models that can capture return-generating processes without relying excessively on restrictive parametric assumptions [5]. The present findings reinforce these conclusions by showing that financial ratios and market indicators remain central predictors, but their effects are better understood when modeled jointly with broader contextual variables.

The significance of the economic variables identified in this study can be explained by the strong sensitivity of listed companies to macroeconomic conditions. Inflation affects production costs, purchasing power, nominal revenues, working capital requirements, and asset valuation. Interest rates influence the cost of debt, investment attractiveness, discount rates, and the allocation of capital between financial assets. Growth in the monetary base and liquidity can affect inflationary expectations, market liquidity, asset prices, and investment behavior. Unemployment and gross domestic product growth reflect broader levels of economic activity, while the Consumer Price Index captures changes in the general price level. The inclusion of these indicators supports the argument that corporate financial performance is partly embedded in the macroeconomic environment and cannot be modeled purely through firm-specific accounting information. This conclusion is compatible with previous evidence demonstrating the influence of macroeconomic and policy-related conditions on corporate financial performance [1]. It also helps explain why nonlinear predictive algorithms may be particularly appropriate for emerging markets, where relationships between macroeconomic variables and stock returns may change across different economic regimes.

The inclusion of social and macro-environmental variables is another notable result. Human capital, the economically active population, and labor force participation represent structural features of the labor market that may affect productivity, consumption, organizational capacity, and long-term growth. Political risk, country risk, and corruption, in turn, influence investor expectations, financing conditions, transaction costs, institutional trust, and the predictability of the business environment. The importance attributed to these variables by experts suggests that financial performance is partly determined by institutional and societal conditions that extend beyond the boundaries of individual firms. This interpretation is broadly consistent with recent research emphasizing that managerial capabilities and digital innovation operate within broader institutional and organizational contexts and may influence perceived financial performance through complex pathways [2]. It is also compatible with research showing that transparency can function as a signal of organizational and financial credibility and shape stakeholder behavior [19]. Thus, the predictive framework developed in the present study reflects a multidimensional understanding of firm performance rather than a narrowly accounting-based perspective.

Another principal finding was the strong predictive performance of ANFIS. The model explained 75.8% of the variance in stock price return on unseen test data, indicating that it captured a substantial proportion of the underlying variability in the target variable. This finding supports previous studies emphasizing the usefulness of artificial intelligence and machine-learning methods in financial prediction. Machine-learning models have been shown to perform effectively in bankruptcy prediction, particularly because they can detect nonlinear interactions among financial indicators that may not be adequately represented by conventional models [10]. Similarly, comparisons between advanced neural-network approaches and traditional methods such as logistic regression have indicated that neural models can provide improved predictive performance in corporate profitability forecasting [9]. The present findings extend this line of evidence by showing that a neuro-fuzzy architecture can also provide strong predictive accuracy for stock price return when multiple categories of explanatory variables are incorporated simultaneously.

The effectiveness of ANFIS may be explained by its hybrid architecture. Conventional statistical models generally require prior assumptions regarding functional relationships, whereas financial data are often nonlinear, noisy, and affected by interaction effects. Artificial neural networks can learn highly complex input-output relationships, but their internal decision processes may be difficult to interpret. Fuzzy systems, in contrast, represent uncertainty through membership functions and rule-based inference but may depend strongly on manually specified parameters. ANFIS combines these advantages by allowing the parameters of the fuzzy system to be optimized through neural learning. This hybrid structure is especially suitable for financial environments because many economic relationships are neither completely deterministic nor purely random. Earlier research applying ANFIS to bankruptcy and financial institution failure prediction demonstrated its capacity to capture complex financial dynamics under unstable conditions [13, 14]. The present study confirms the applicability of this approach to corporate financial performance prediction in the Tehran Stock Exchange.

The findings are also in line with previous research applying neural and neuro-fuzzy systems to stock-return forecasting. Raoofi and Mohammadi showed that combining wavelet decomposition with an adaptive neuro-fuzzy network could be effectively used to predict Tehran stock market returns [17]. Similarly, estimates of stock exchange returns using different neural-network architectures have demonstrated that computational intelligence methods can capture market patterns that may be difficult to detect through conventional approaches [16]. The use of neural fuzzy systems for predicting annual corporate returns has likewise provided evidence for the usefulness of hybrid intelligent models in corporate forecasting [18]. These studies support the present conclusion that stock returns can be modeled more effectively when algorithms are capable of adapting to nonlinearities, uncertainty, and multidimensional inputs.

The observed prediction errors also warrant discussion. Although the ANFIS model closely tracked the overall trend of stock returns, its errors increased for observations with exceptionally high or low returns. This finding is unsurprising from a machine-learning perspective. Extreme values tend to occur less frequently in training datasets and therefore provide the model with fewer opportunities to learn their underlying patterns. Such values may also arise from exceptional market events, unexpected policy decisions, firm-specific shocks, or speculative behavior that are not fully represented by the selected input variables. Previous studies of financial prediction have noted that model performance can be sensitive to the composition and distribution of the data, especially when observations are highly heterogeneous [11]. Similarly, adaptive forecasting approaches have been developed specifically because financial relationships can change dynamically over time and require models capable of updating as new information emerges [15]. Consequently, the slightly higher error at distributional extremes does not negate the utility of the model but indicates an area in which further refinement may improve forecasting precision.

The application of a fuzzy Delphi procedure before ANFIS modeling represents another important contribution of the study. Many predictive studies begin directly with a large set of candidate variables selected solely from available datasets. Such an approach can introduce irrelevant predictors, multicollinearity, unnecessary model complexity, and reduced interpretability. In contrast, the present research combined literature-based identification with expert evaluation and consensus-building before model construction. This allowed the input variables to be screened not only statistically but also substantively according to their relevance to the Iranian capital market. This strategy is consistent with fuzzy decision-making research showing that expert-based methods can effectively identify influential factors in complex financial systems [1]. It also complements broader applications of artificial intelligence in management, where effective implementation depends on the integration of technological capability with expert knowledge, organizational context, and decision-making processes [6, 7].

The findings also have implications for the broader literature on digital transformation and intelligent decision support. Artificial intelligence is increasingly used not simply as an analytical tool but as part of organizational capability development. Research has shown that AI-related innovation can improve organizational and financial outcomes through enhanced efficiency, decision quality, operational responsiveness, and innovation [8]. Likewise, digital transformation and intellectual capital have been linked to improved financial performance through knowledge integration and more efficient resource utilization [3]. The current study extends these insights to capital-market forecasting by demonstrating that intelligent systems can integrate heterogeneous financial and non-financial information into a coherent predictive structure. The capacity of neural networks to model complex project outcomes in other management contexts further indicates that their usefulness is not confined to finance but reflects a more general capacity to learn nonlinear organizational processes [21].

The role of data interpretation and visualization should also be considered in explaining the utility of intelligent models. Advanced computational models often generate complex outputs that require clear interpretation if they are to support managerial decision-making. Research on artificial intelligence and sentiment analysis has shown that visualization and explanatory presentation can improve the comprehensibility of machine-generated results [20]. In the present study, comparing actual and predicted stock returns for selected firms provided a direct and interpretable demonstration of model performance. Such presentation is useful because predictive accuracy alone may not be sufficient for managers and investors; users also need to understand where a model performs strongly and under what conditions its errors increase.

Finally, the expert validation results provided complementary evidence regarding the credibility of the developed model. The mean internal validity score was 4.13 out of 5 and the mean external validity score was 4.11, with all components significantly exceeding the midpoint of the scale. The highest internal validity score was obtained for logical review, whereas sensitivity analysis received the lowest score, although it remained at a high level. For external validity, the objective dimension received the highest evaluation, while control of confounding variables obtained the lowest. These findings suggest that experts regarded the model as logically coherent, methodologically appropriate, generalizable, and practically applicable. This qualitative confirmation is important because predictive systems intended for managerial and investment use should be assessed not only according to numerical accuracy but also according to their substantive plausibility and usefulness. The convergence between quantitative model performance and qualitative expert evaluation strengthens confidence in the overall validity of the proposed framework.

The present study has several limitations that should be considered when interpreting its findings. First, the quantitative sample was restricted to companies listed on the Tehran Stock Exchange that met the specified screening criteria, and financial institutions, banks, insurance companies, and investment firms were excluded because of their different financial structures. Therefore, the findings may not be directly generalizable to all industries or to non-listed companies. Second, although the study incorporated a relatively broad set of financial, economic, social, and macro-environmental variables, other potentially influential factors such as exchange-rate volatility, industry competition, corporate governance characteristics, management quality, investor sentiment, technological capability, and firm-specific strategic events were not directly included. Third, the qualitative phase relied on a relatively small expert panel, which is appropriate for fuzzy Delphi research but may still reflect the judgments of a limited professional group. Fourth, extreme stock returns were relatively uncommon in the dataset, which may have reduced the model's ability to predict unusually high or low observations with the same accuracy as more typical cases. Finally, the study was based on historical data, and structural breaks or exceptional economic events may alter future relationships among the predictors and financial performance.

Future studies are recommended to evaluate the proposed framework in other capital markets and across different economic environments in order to assess the stability and generalizability of the identified predictors. Researchers could also compare ANFIS directly with alternative machine-learning and deep-learning methods, including gradient boosting, random forests, support vector machines, recurrent neural networks, long short-term memory networks, and transformer-based forecasting architectures. Future studies could incorporate additional predictors such as exchange rates, corporate governance indicators, board characteristics, ownership structure, investor sentiment, environmental performance, innovation capability, digital maturity, and industry-level competition. Separate models could also be developed for different industries to determine whether the relative importance of predictors varies across sectors. In addition, expanding the expert panel and using multiple rounds of external validation could strengthen the qualitative component of the framework. Finally, future research could employ rolling-window or online-learning procedures to allow model parameters to adapt continuously to changing economic and market conditions and could examine whether specialized methods for handling outliers and extreme market movements improve prediction accuracy.

Managers, investors, financial analysts, and capital-market institutions can use the findings of this study to develop more comprehensive financial monitoring and forecasting systems. Rather than relying exclusively on historical accounting ratios, decision-makers should integrate firm-level indicators with macroeconomic, labor-market, and institutional risk measures when evaluating future performance. Financial managers can use intelligent prediction systems as early-warning tools to detect potential deterioration or improvement in market performance and to support financing, investment, liquidity, and risk-management decisions. Investors and portfolio managers can incorporate ANFIS-based forecasts into screening and asset-allocation processes while continuing to consider the possibility of larger errors during extreme market conditions. Regulatory bodies and stock exchanges can encourage standardized access to high-quality financial and macroeconomic datasets to facilitate the development of more reliable predictive systems. Organizations should also establish periodic model-retraining procedures so that prediction systems remain responsive to structural changes in the economy and capital market. Most importantly, intelligent forecasting models should be used as decision-support tools in conjunction with professional judgment rather than as substitutes for managerial or investment expertise.

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.

References

[1] E. Alizadeh, H. Vakilifard, and M. Hamidian, "Examining Micro- and Macro-Level Economic Policy Factors Affecting Firms' Financial Performance: A Fuzzy DEMATEL Approach," (in English), *Scientific Research Quarterly of Investment Knowledge,* pp. 11-41, 2022.

[2] C. A. Asamoah, K. N. Takyi, A. Klapalová, I. Agirre-Aramburu, and J. Matošková, "Dynamic managerial capabilities, digital innovation and perceived financial performance in the banking sector," *Scientific African,* vol. 31, 2026, doi: 10.1016/j.sciaf.2025.e03157.

[3] J. Yin and J. Xu, "Intellectual capital, digital transformation and firms' financial performance: Evidence from ecological protection and environmental governance industry in China," *PLoS ONE,* vol. 20, no. 1, p. e0316724, 2025, doi: 10.1371/journal.pone.0316724.

[4] H. Khalouzadeh and N. Amiri, "Determining the Optimal Stock Portfolio in the Iranian Stock Market Based on Value-at-Risk Theory," (in English), *Economic Research,* no. 73, p. 231, 2020.

[5] H. Ghalibaf Asl, R. Tehrani, M. Rostami, and A. Siri, "Designing a Model for Predicting Long-Term Stock Returns Using Nonparametric Simulation of Bond Returns," (in English), *Financial Management Perspective,* vol. 8, no. 1, pp. 133-155, 2023.

[6] S. Akbari Emami, M. Jamipour, and S. Fathi, "Designing a Framework for the Application of Artificial Intelligence in Human Resource Management," (in English), *Biannual Scientific Journal of Sustainable Human Resource Management,* vol. 5, no. 9, pp. 263-284, 2023.

[7] B. Trenerry *et al.*, "Preparing Workplaces for Digital Transformation: An Integrative Review and Framework of Multi-Level Factors," *Frontiers in Psychology,* vol. 12, p. 620766, 2021.

[8] Y. Wang and F. Liu, "Impact of artificial intelligence innovation on food company performance," *International Review of Financial Analysis,* vol. 103, no. 5, pp. 1115-1145, 2025, doi: 10.1016/j.irfa.2025.104219.

[9] S. H. Hosseini and S. Abbasi, "Comparing the Efficiency of Artificial Intelligence Models Based on Deep Neural Networks and Logistic Regression in Predicting Corporate Profitability," (in English), *Accounting and Auditing Review,* vol. 30, no. 2, pp. 221-245, 2024.

[10] F. Barboza, H. Kimura, and E. I. Altman, "Machine learning models and bankruptcy prediction," *Expert Systems with Applications,* vol. 83, pp. 405-417, 2017, doi: 10.1016/j.eswa.2017.04.006.

[11] F. M. Richardson and L. F. Davidson, "An exploration into bankruptcy Discriminant model sensitivity," *Journal of Business Finance & Accounting,* vol. 10, no. 2, pp. 195-207, 2020.

[12] M. Ansari and R. Rahimi, "Predicting Financial Performance and the Probability of Distress in Companies Listed on the Tehran Stock Exchange Using Gradient Boosting Algorithms," (in English), *Financial Accounting and Auditing Research,* vol. 15, no. 58, pp. 85-112, 2023.

[13] N. Arora and J. R. Saini, "Time series model for bankruptcy prediction via adaptive neuro-fuzzy inference system," *International Journal of Hybrid Information Technology,* vol. 6, no. 2, pp. 51-63, 2013.

[14] W. Choensawat and P. Polsiri, "Financial institution failure prediction using adaptive neuro-fuzzy inference systems: Evidence from the East Asian economic crisis," *Journal of Advanced Computational Intelligence and Intelligent Informatics,* vol. 17, no. 1, pp. 83-91, 2013, doi: 10.20965/jaciii.2013.p0083.

[15] T. Buisui, "Adaptive Kalman filter optimization," *Journal of International Money and Finance,* vol. 42, no. 3, pp. 311-331, 2022.

[16] D. Liong, R. Honka, and J. H. Chintagunta, "Estimates of the return on the Taiwan Stock Exchange using different neural networks," *Applied Intelligence,* vol. 22, no. 1, pp. 47-60, 2023.

[17] A. Raoofi and T. Mohammadi, "Predicting Tehran Stock Market Returns Using a Combination of Wavelet Decomposition and Adaptive Neuro-Fuzzy Network," (in English), *Iranian Economic Research,* vol. 23, no. 76, pp. 107-136, 2023.

[18] R. Triankel, "Application of Neural Fuzzy System and Neural Network for predicting annual returns of construction companies," *IEEE Transactions on Knowledge and Data Engineering,* no. 26, pp. 866-883, 2023.

[19] Z. Wu and Y. Dai, "Signal of Financial or Performance Transparency? The Impact and Mechanisms of Nonprofit Transparency on Donation Willingness," *Public Performance & Management Review,* vol. 48, no. 3, pp. 675-704, 2025, doi: 10.1080/15309576.2025.2465750.

[20] R. Jain *et al.*, "Explaining sentiment analysis results on social media texts through visualization," *Multimedia Tools and Applications,* vol. 82, no. 15, pp. 22613-22629, 2023.

[21] D. GorsenT, L. Kauf, and D. J. Hand, *Application of artificial neural network model in predicting the time of construction projects*. UK: John Wiley and Sons, 2024.