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Development of a comprehensive model to predict stock prices in the stock market with an interpretive structural modeling approach

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Abstract Predicting stock prices has long been a topic of interest for analysts and researchers. The aim of this study is to develop a comprehensive model for predicting stock prices in the Tehran Stock Exchange using a combined approach of fuzzy Delphi interpretive structural modeling with the use of technical, fundamental, macroeconomic, and emotional factors. In this study, first, using the fuzzy Delphi method, 15 key criteria were identified from among 54 prediction criteria extracted from research literature according to investors' perspectives. Then, using the interpretive structural modeling approach, the relationships between them were examined and a hierarchical model was presented. Based on the findings in the ISM model, it is observed that the price is placed at the end of the hierarchy with high driving power, depending on earnings per share and cash flow index. The criteria that are placed at the bottom of the hierarchy are exchange rates and relative strength index and exponential moving average, which are the most influential indicators. This study is the first of its kind to identify stock price prediction criteria by considering all dimensions and developing hierarchical relationships between them using the ISM approach

Keyword: Stock Market, Stock Price Prediction Indicators, Fuzzy Delphi Approach, Interpretive Structural Modeling, Comprehensive Model.

1 Introduction

Financial predictions have always been an exciting area of research for investors, market analysts, and the general public as it presents opportunities to increase wealth. In financial markets, various assets such as stocks, bonds, currencies, and commodities are traded at prices determined by market forces

Among different assets, stocks have received more attention due to their higher returns and portfolio management, based on short-term or long-term market price predictions. Generally, stock price predictions are based on four terms of thought, in which technical and

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fundamental analysis has received more attention than others. In technical analysis, the development of stock prices is predicted through the analysis of historical market data such as price and volume, and various technical indicators such as stochastic oscillator, moving average, and relative strength index (RSI) are used in prediction models. The effectiveness of these input features for predicting future stock markets is studied. A large part of the research has focused on technical analysis [1-4].

Fundamental analysis relies on a company's technical analysis and fundamental information Such as market position, costs, and annual growth rates. Over the past 80 years, fundamental analysis has developed several methods to determine intrinsic value, which is the actual value that investors invest in for a longer period of time. This analysis is a science that is constantly evolving and becomes more stable with the emergence of newer methods [5]. However, fundamental analysis is not very popular among market analysts because unlike technical analysis, which is easier to use and does not require a high level of economic knowledge, it is very complex and requires extensive knowledge and science. Although technical analysis provides a framework for studying investor behavior, fundamental analysis provides a mechanism for evaluating the financial status of an investment.

They have used various macroeconomic factors such as commodity prices, market history, and foreign exchange rates to predict the direction of the Mumbai stock market. In another study. Campbell [6] used financial indicators that were a combination of technical and fundamental indicators to select optimal stocks in the Taiwan stock market. However, Campbell and Shiller [7] challenged the efficient market hypothesis Campbell and Viceira [8] and the accepted random walk hypothesis Malkiel [9] using various artificial intelligence algorithms and found that future changes in stock prices cannot be predicted from historical data because they are independent and random fluctuations. Therefore, future changes in stock prices are widely considered unpredictable. However, many financial economists, researchers, and traders believe that stock prices are at least somewhat predictable because price changes tend to repeat due to collective investors' behavior and patterns [10].

The third method is macroeconomic factors that focus on inflation rates, currency and oil markets, and ultimately, the current stock market is affected not only by historical prices but also by the mood of society. The general social mood regarding a company may be one of the important variables that affect its stock price [11]. Understanding the changing order in the stock market and predicting the trend of stock prices has always been of interest to investors and researchers. The increase and decrease in stock prices are influenced by many factors such as politics, economy, society, and the market [12]. For stock investors, predicting the trend of the stock market is directly related to earning profits. The more accurate the prediction is, the more effectively it can prevent risks. For companies listed on the stock exchange, stock prices not only affect the operational conditions of the company and expectations of future development but also serve as an important technical indicator for analyzing and researching the company. Stock prediction research also plays an important role in the economic development research of a country. Theoretically, there are hidden factors that guide systematic changes in stock returns without being directly observable. Therefore, many researchers have suggested predictors as representatives of these hidden and unobservable factors, such as valuation ratios like stock earnings yield [13], dividend payout ratio [14, 15] as well as nominal interest rates [16], inflation rates [17, 18].

The present study aims to convert the various coordinates present in individuals' mental background for understanding the intertwined elements of stock price prediction into clear and specific relationships using a combination of fuzzy Delphi methods and interpretive structural modeling, based on feedback relationships between influential predictors and

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theoretical foundations related to the field of stock price prediction. By using central relationships and the degree of influence of these predictors, decision-makers can correctly respond to two areas of effective criteria and their level of grading based on their impact on stock price prediction. Overall, the findings of this study can provide a hierarchical model for investors to investigate the susceptibility and impact of various factors, including technical, fundamental, macroeconomic, and behavioral dimensions, which have a significant impact on stock price prediction.

In continuation, the theoretical foundations and research background are first mentioned, followed by a detailed explanation of the research method, including data collection tools, statistical population, and applied methods. Finally, the research findings, conclusions, and recommendations are presented.

2 Theoretical Foundations and Research Background

Stock market prediction is one of the most popular topics in academic research and real-world trading. Many studies have attempted to answer the question of whether the stock market can be predicted. Some research has been based on the random walk theory and the efficient market hypothesis (EMH). According to EMH [19], the current stock market fully reflects all available information. Therefore, price changes occur purely due to new information or news. Since news occurs randomly and is currently unknown, stock prices should follow a random pattern, meaning the best estimate for the next price is the current price. As a result, they cannot be predicted with an accuracy greater than 50% [20].

On the other hand, various studies indicate that stock prices do not follow purely random steps and are somewhat predictable [21, 22, 23]. Recent research utilizing machine learning and deep neural networks has further explored this issue, showing that recognizable patterns exist in financial data that can improve the accuracy of stock price predictions [24, 25].

However, the ambiguous nature of stock index fluctuations inherently makes investments risky, making it difficult for investors and governments to assess market conditions. Since stock indices are generally dynamic, nonlinear, and non-parametric, accurately predicting their movement in the long run remains a highly challenging and significant issue [26]. Market participants seek methods that allow them to predict future stock prices to maximize their returns. Therefore, it is essential to develop reliable, scientifically sound methods for stock price forecasting to guide investors.

Factors Affecting Stock Price Prediction

Based on previous studies, the factors influencing stock price movements are generally categorized into four main groups:

1. Fundamental Factors: Examining financial statements, financial ratios, and a company's economic conditions

2. Technical Factors: Analyzing price charts, trading patterns, and technical indicators

3. Macroeconomic Factors: Assessing variables such as inflation, interest rates, oil prices, and exchange rates

4. Psychological and Behavioral Factors: Evaluating investor sentiment, financial news, and media data

1. Fundamental Analysis and Financial Variables

Jiang et al. [27], Lim et al. [28], Shabbir and Muhammad [29], Tehrani et al. [30] used liquidity, activity, leverage, and profitability ratios in their research. The most commonly used ratios included the current ratio, quick ratio, debt-to-equity ratio, debt-to-assets ratio, accounts

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receivable turnover, asset turnover, return on assets, return on equity, price-to-earnings (P/E) ratio, and price-to-book ratio.

Recent studies suggest that integrating deep learning with fundamental analysis can enhance stock selection accuracy. Siew et al. [31] used a combination of fundamental and technical variables, including return on investment, asset-to-debt ratio, trading volume, and gross income, in their stock forecasting model. This study randomly selected 60 stocks from the U.S. stock market and applied factor analysis and clustering techniques to rank stocks based on their financial attributes.

2. Technical Analysis and Machine Learning Approaches

Research has shown that technical analysis using indicators such as moving averages, RSI, and Bollinger Bands can enhance prediction accuracy [32]. Machine learning models, particularly recurrent neural networks (RNNs) and deep learning, have demonstrated superior performance compared to traditional methods [33].

Furthermore, the Gated Three-Tower Transformer (GT3) model, introduced in 2023, has shown that combining market data with financial news and media sentiment can significantly improve forecasting accuracy [34].

3. Psychological Analysis and Social Media Data

Sentiment analysis has recently gained traction as a crucial factor in stock price forecasting. Muhammad et al. [35] demonstrated that analyzing financial news and social media data could predict market trends. Their study utilized a dataset comprising 265,000 financial news articles and daily stock prices of S&P 500 companies over five years, proving that deep learning models for natural language processing (NLP) improve predictive accuracy.

Moreover, recent studies in 2024 have revealed that leveraging Transformer-based models such as BERT and GPT for analyzing financial tweets can provide strong signals for price fluctuations [36].

4. Combining Fundamental, Technical, and Sentiment Analysis

Some studies have suggested that Bettman et al. [37] proposed a model that combined fundamental and technical analysis for stock valuation, confirming that both methods are complementary rather than substitutive.

Recent studies [38, 39] also indicate that integrating fundamental, technical, and sentiment analysis can enhance stock price predictions. Specifically, hybrid AI models incorporating financial data, news sentiment, and social media insights outperform traditional forecasting models.

3 Research Methodology

This study is descriptive-survey in terms of methodology and applied in terms of purpose. The statistical population in this study was examined from two perspectives: investors and university experts. Naturally, investors who predict and invest in the stock market by

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examining technical, fundamental, and macroeconomic indicators are familiar with financial indicators and their number is small, so they are considered experienced investors. In this study, investors with the following conditions were selected: (1) at least 5 years of familiarity with the stock market, (2) having a master's degree or higher in fields related to accounting and finance. Therefore, 12 experienced investors were selected based on the above conditions. From the perspective of research experts, the statistical population included university professors in the fields of accounting and finance with the rank of assistant professor or higher, who were selected as research experts.

In this study, first, questionnaires containing 54 criteria related to predicting stock prices were provided to experts to determine the importance of criteria based on a Likert spectrum from very low (1) to very high (5). After summarizing the responses received, 15 criteria with higher importance than the average (number 3) were selected to predict stock prices in the stock market. After receiving the responses, using fuzzy Delphi method, 15 key criteria effective in predicting stock prices in the Tehran Stock Exchange were extracted. Finally, to examine the relationships between the extracted key criteria, a questionnaire was prepared and provided to 10 university experts and they were asked to determine the relationships between the criteria based on theoretical foundations. Ultimately, based on the received responses and using structural interpretive modeling method, the relationships between the criteria were examined and the fundamental criteria were identified.

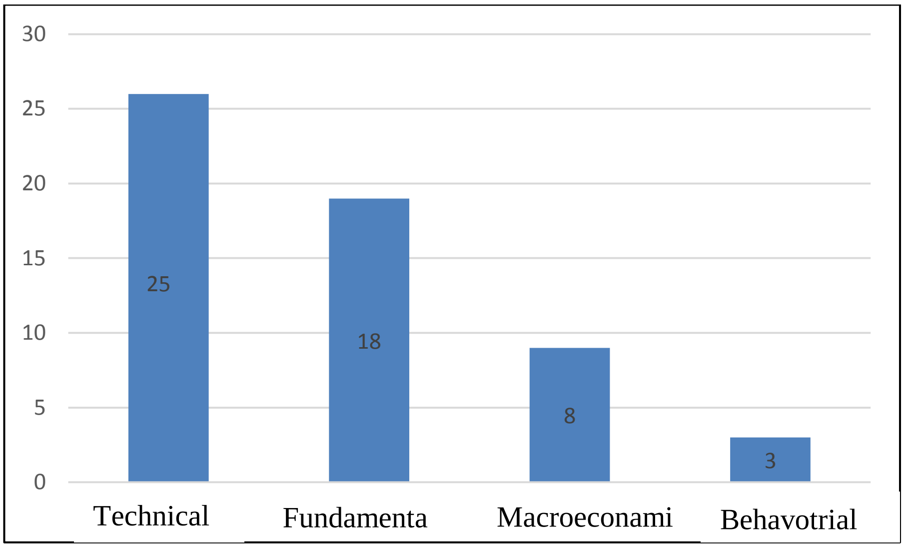

Fig. 1 Method of **distributing** selected criteria

Based on diagram 1: the extracted components include 25 technical dimension components, 18 fundamental dimension components; it includes 8 macroeconomic components and 3 behavioral components, and the components are started in table 1. Components of stock price prediction:

Table 1 Components of stock price prediction

Behavioral Components	**Technical indicators**	**Fundamental components**	**Macro-economic indicators**
Number of transactions	Average true range indicator	Operation profit growth (OPG)	Exchange rate
Trading volume	Simple moving average		Global oil price
Number of traders			

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involved in transactions	indicator Exponential moving average indicator Weighted moving average indicator Divergence/ convergence moving average indicator Directional moving average Bollinger bands indicator Price channel indicator Relative strength index Volume balance indicator Cash flow index indicator Stochastic k% indicator Stochastic D% indicator Fast stochastic D% indicator Aroon indicator Moving momentum indicator True range moving average index Williams R% indicator Rate of change indicator Accumulation/ distribution indicator Dispersion index Dispersion index Increase/ decrease line Price indicator Lowest and highest price indicators	Price-to-earnings ratio (P/E) Operation profit margin Net profit margin Company sales growth rate Foreign sales volume (exports) Domestic sales volume Stock buying power to sales ratio Sales volume Export to sales ratio Capital turnover ratio Divided per share (DPS) Return on equity (ROE) Money flow index (MFI) Return on assets (ROA) Demand index (DI) Current debt to equality ratio Earnings per share (ESP)	Price of global per ounce Volume of money Consumer price index growth rate Unemployment rate Average inflation rate Gross domestic product (GPD)

The following data analysis methods were used in this study:

The fuzzy Delphi method, introduced by Ishikawa et al. (1993), is based on the traditional Delphi method and fuzzy set theory. Due to the high implementation costs and the risk of filtering unique expert opinions by the organizers, expert opinions have traditionally been less convergent with the Delphi approach. To address some of the uncertainties, the fuzzy Delphi panel, FDM, which is a combination of the Delphi consensus panel and fuzzy set theory (FST), is used, as well as membership degree to determine the membership function of each participant. Therefore, FDM can be used to evaluate the importance of parameters and also for screening key criteria.

In the first step, the fuzzy Delphi method is used to select key criteria for predicting stock prices from among 54 selected criteria. The first stage of this process is to select experienced individuals. In this study, 10 experienced individuals in the field of stock and securities exchange and university professors were used, and the necessary preparations will be made to implement the process. Next, questionnaires are sent to these experienced individuals. After completion, the results are collected and sent back to them again in the form of a questionnaire for them to provide feedback on the initial results. After collecting and analyzing the opinions of the experts in the second round, the average difference is examined. If this difference is less than 0.2, consensus has been reached and the fuzzy Delphi process is completed. Otherwise, the results of this round will be analyzed again and sent to the experts.

This back-and-forth process continues until the expert's reach consensus on all criteria. If experts decide to add a criterion during this process, it will be added to the questionnaire in the next round and opinions will be obtained on that criterion. Finally, to confirm and screen the criteria, the value of each criterion's acquisition value is compared to the threshold value.

The threshold value is calculated in several ways, but generally a value of 0.7 is considered as the threshold value. To do this, first, the triangular fuzzy values of the expert opinions are calculated, and then the fuzzy mean of n respondents' opinions is estimated to calculate the average opinion. In this study, triangular fuzzy numbers from Table were used to convert linguistic terms into triangular fuzzy number1.

Table 2 linguistic terms and their fuzzy values based on a 5 point likert scale spectrum

Fuzzy values	Linguistic terms
(0.75, 0.75, 1)	Very high impact
(0.50,0.75,0.1)	High impact
(0.25,0.50,0.75)	Moderate impact
(0.00,0.25,0.50)	Low impact
(0.00,0.00,0.25)	Very low impact

3.1 Interpretive Structural Modeling (ISM)

Interpretive Structural Modeling (ISM) is used to determine the relationship between selected factors (indicators). Through ISM, a group of different but directly related factors are placed In a well-defined systematic model. ISM helps to build a comprehensive multi-level model by dividing a complex set of factors into smaller sets of factors (Hussein et al., 2021), and as a result, it is possible to convert undefined models into well-defined models. The steps takenfor the ISM method are as follows:

Formation of Structural Self-Interaction Matrix (SSIM)
In this step, experts consider criteria pairwise and respond to pairwise comparisons based on the following spectrum.

Obtaining the initial accessibility matrix
By converting the symbols of the SSIM matrix into zeros and ones, the initial accessibility sub-matrix is obtained.

Making the accessibility matrix compatible
After obtaining the initial accessibility matrix, its internal compatibility must be established.

Determining the levels of variables
In this step, the researcher calculates the input (prerequisite) and output (accessibility) criteria set for each criterion and then identifies common factors. In this step, the criterion with the highest level is the one where the output set matches the common set. After identifying this

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variable or variables, its row and column are removed from the table and the relevant operation is repeated on the other criteria.

Drawing interaction network

In this step, an interaction network is created based on the levels of criteria and their relationships. Using the levels obtained from the criteria, ISM interaction network is drawn. If .there is a relationship between two variables i and j, it can be shown by a directional arrow.

Data analysis

Identification of stock price prediction criteria using fuzzy Delphi method In the first round of the fuzzy Delphi method, after studying and reviewing research literature and previous research findings and a thorough study of theoretical concepts of stock price prediction from four different perspectives: technical components, fundamental components, macroeconomic components, and psychological and behavioral components, they were identified. Then, to determine the priority or importance of different indicators, a questionnaire was used to collect the opinions of research experts. In the questionnaire developed to determine the relative importance of each indicator, a five-point Likert scale was used. In each perspective, indicators that had the highest average importance were selected. The results of the questionnaires showed that out of 55 indicators, 15 indicators were more important than other indicators. In the second round, to calculate the importance of criteria for stock price prediction from the experts' point of view, a questionnaire was sent to 10 university experts again, and they were asked to express their opinions.

Table 3 The result of the second round of the fuzzy logic method for predicting stock prices in the stock market

Confirmed	Difference between average expert opinions	Average expert opinions	Very high (0.75, 0.75, 1)	High (0.50, 0.75, 1)	Mode rate (0.75, 0.50, 0.25)	Low (0.25, 0.50, 0.75)	Very low (0, 0, 0.25)	Linguistic value: Fuzzy value criterion	Linguistic value: Criterion code
Confirmed	0.8	0.5	0	4	5	7	4	Exponential moving average indicator	1
Rejected	0.1	0.6	2	5	5	5	3	of the average correct range	2
Rejected	0.11	0.6	7	8	4	1	0	Williams R% indicator	3
Rejected	0.1	0.9	8	6	4	1	1	Rate of change indicator	4
Rejected	0.09	0.4	1	3	4	1	3	Accumulation/ distribution indicator	5
	0.1	0.6	1	6	5	5	4	Average true range index	6
Confirmed	0.12	0.8	10	7	2	0	1	Demand index (DI)	7
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
Rejected	0.1	0.5	0	4	5	4	7	Number of traders involved in transactions	52
Confirmed	0.1	0.9	5	7	6	1	1	Price-to-	53

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								earnings ratio (P/E)	
Confirmed	0.1	0.8	8	7	2	2	1	Trading volume	54

Given that in this round, the average difference between experts' opinions is less than 2.0, consensus has been reached and 15 criteria have been identified as essential indicators for predicting stock prices on the stock exchange. These include moving average, price channel indicator, relative strength index, balanced trading volume indicator, price indicator price-to-earnings ratio (P/E), operating profit-to-sales ratio, gross profit-to-sales ratio, company sales growth rate, buying and selling stocks, dividend per share (DPS), money flow index (MFI), earnings per share (EPS), exchange rate, and trading volume, which are shown in table 3.

3.2 Designing the model using Interpretive Structural Modeling (ISM) method

Step 1 - Determining the variables used in the model: In this step, to examine the relationships between the selected indicators, 15 indicators extracted by the fuzzy Delphi method (Table 4) were used with the ISM technique. Initially, a 15x15 matrix was prepared based on the responses of 10 investment experts and university professors to form the initial matrix. The rows and columns of the initial matrix include 15 indicators for predicting stock prices, namely moving average, price channel indicator, relative strength index, balanced trading volume indicator, price indicator, price-to-earnings ratio (P/E), operating profit-to-sales ratio, gross profit-to-sales ratio, company sales growth rate, buying and selling stocks, dividend per share (DPS), money flow index (MFI), earnings per share (EPS), exchange rate, and trading volume.

Step 2 - Formation of SSIM: A pairwise comparison matrix has been created for the 15 identified criteria. Textual relationship indicators have been obtained from industry experts to establish textual relationships between criteria. The textual relationship indicators that provide pairwise relationships between different criteria can be described using V, A, X, and O.

V means that criteria I lead to criteria j.
A means that criteria j results in criteria i.
X means that criteria I and j are related to each other.
O means that criteria I and j are not related to each other.

The results are shown in Table 5.

Step 3 - Creating the initial reachability matrix: In this step, the self-interaction structural matrix is converted to a binary matrix to obtain the initial reachability matrix. The values of V, A, X, and O are replaced with 1 and 0 to create the initial reachability matrix (Table 6) by following the rule below If the input cell (i, j) in SSIM is V, the input cell (i, j) in the reachability matrix becomes 1 and the input cell (j, i) becomes 0. If the input cell (i, j) in SSIM is A, the input cell (i, j) in the reach ability matrix becomes 0 and the input cell (j, i) becomes 1. If the input cell (i, j) in SSIM is X, both the input cell (i, j) and the input cell (j, i) in the reachability matrix become 1. If the input cell (i, j) in SSIM is O, both the input cell (i, j) and the input cell (j, i) in the reachability matrix become 0.

Step 4 - Creating the final reachability matrix (Aligning the reachability matrix): In this step, all secondary relationships between variables were examined, and the final reachability matrix (FRM) was obtained according to Table 7. In this table, the penetration power and dependence power of each variable are shown. The penetration power of a variable is obtained by adding the number of variables affected by it and the variable itself. Also, the dependence power of a variable is calculated by adding the variables that it affects and itself.

Table 4 Stock price prediction criteria and sub criteria

Criteria		Sub-criteria	Criteria		Sub-criteria
Technical dimension components	C1	Exponential moving average	Macroeconomic components	C14	Exchange rate
	C2	Power channel indicator	The components of the behavioral dimention	C15	Volume of trading
	C3	Comparative			
	C4	Balanced volume indicator Balanced trading			
	C5	Price indicator			
Fundamental components	C6	Operating profit to sales ratio			
	C7	Operating profit ton sales ration			
	C8	Gross profit to sales ratio			
	C9	Company sales growth			
	C10	Earnings per share			
	C11	Cash follow index			
	C12	Earnings per share			
	C13	Buy stock to sell			

Table 5 Criteria for each view

Criterion code	View	row
C1, C2, C3, C4, C5,	Technical	1
C6, C7, C8, C9, C10, C11, C12, C13	Fundamental	2
C14	Macro	3
C15	Behavioral	4

Table 6 Self interactive structural matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	-	A	A	O	O	O	O	A	A	O	V	O	O	A	A
C2		-	V	O	O	O	O	O	O	O	O	O	O	O	X
C3			-	V	O	O	O	O	A	O	V	A	O	X	A
C4				-	O	A	O	V	O	V	V	O	V	V	A
C5					-	O	X	O	X	A	V	O	O	O	O

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C6						-	O	O	O	O	V	V	V	V	V
C7							-	O	X	O	V	O	O	O	O
C8								-	A	O	X	O	O	A	A
C9									-	X	V	O	O	O	O
C10										-	O	O	O	O	O
C11											-	A	A	A	A
C12												-	X	X	O
C13													-	X	O
C14														-	V
C15															-

Table 7 Access matrix

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**
C1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
C2	1	1	۱	0	0	0	0	0	0	0	0	0	0	0	1
C3	1	0	1	1	0	0	0	0	0	0	1	0	0	1	0
C4	0	0	0	1	0	0	0	1	0	1	0	0	1	1	0
C5	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0
C6	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
C7	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0
C8	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
C9	1	0	0	1	0	0	0	1	1	0	1	0	0	0	0
C10	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
C11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
C12	0	0	1	0	0	0	0	0	0	0	0	1	1	1	0
C13	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
C14	1	0	0	0	0	0	0	0	0	0	1	1	1	1	1
C15	1	1	0	1	0	0	0	1	0	0	1	0	0	1	1

Table 8 final access matrix

Penetration power	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	
C1	1	0	1	0	0	1	0	1	0	1	1	1	1	1	1	10
C2	1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	12
C3	1	0	1	1	0	0	0	1	0	1	1	1	1	1	1	10
C4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
C5	1	0	1	0	1	0	1	1	1	1	1	0	0	0	0	8
C6	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1
C7	1	0	1	0	1	0	1	1	1	1	1	0	0	0	0	8
C8	1	0	0	0	0	0	1	1	0	1	1	0	0	0	0	5
C9	1	0	1	1	1	0	1	1	1	1	1	0	0	1	0	10
C10	1	0	1	0	1	0	1	1	1	1	1	0	0	0	0	8
C11	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1

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															2
C12	1	0	1	1	0	0	0	1	0	0	1	1	1	1	1	9
C13	1	0	1	0	0	0	0	1	0	0	1	1	1	1	1	8
C14	1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	12
C15	1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	12
Power of dependency	15	5	13	8	9	3	9	15	5	12	15	9	9	10	9	

Step 5 - Leveling: The final reachability matrix was used to calculate the set of accessibility and prerequisite sets. Additionally, the intersection of these sets was calculated for each index.

The accessibility set is equal to the row of each criterion (the number of "1"s in each column of FRM), and the prerequisite set is equal to the column of each criterion (the number of "1"s in each row of FRM). Each level is identified when the intersection of the accessibility and prerequisite sets is equal to the accessibility set. Then, those factors are removed from the table, and this process continues for other variables until all criteria are placed in their specific levels. The number of levels will be equal to the number of repetitions. Factors that have the same accessibility and intersection set are placed at the top level in the ISM hierarchy. The remaining levels are identified by continuing the same process. These levels help to build the final ISM model, which is classified into 8 levels and displayed in figure 2.

Table 9 leveling of indicators

Row	Exit	Entrance	Share	Level
1	1-3-6-8-10-11-12-13-14-15	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22	1-3-6-8-10-11-12-13-14-15	2
2	1-2-3-4-7-8-10-11-12-13-14-15	2-4-6-14-15	2-4-14-15	5
3	1-3-4-8-10-11-12-13-14-15	1-2-3-4-5-6-7-9-10-12-13-14-15	1-3-4-8-9-10-12-13-14-15	2
4	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15	2-3-4-6-9-12-14-15	2-3-4-6-9-12-14-15	3
5	1-3-5-7-8-9-10-11	4-5-6-7-9-10	5-7-9-10	7
6	1-4-6	1-2-3-4-5-6-8-10-11-12-13-14-15	1-4-6	8
7	1-3-5-7-8-9-10-11-12	2-4-5-7-8-9-10-14-15-16	5-7-8-9-10	6
8	10-11-12-1-7-8-9	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15	10-11-12-1-7-8-9	4
9	1-3-4-5-7-8-9-10-11-14	4-5-7-9-10	4-5-7-9-10	6
10	1-3-5-7-8-9-10-11-12	1-2-3-4-5-6-7-8-9-10-14-15	1-3-7-8-9-10	5
11	1-8-11	1-2-3-4-5-6-7-8-9-10-11-12-13-14	1-8-11	8
12	1-3-4-5-8-11-12-13-14-15-17-19-21-22	1-2-3-4-6-12-13-14-15	1-3-4-12-13-14-15	4
13	1-3-8-11-12-13-14-15	1-2-3-4-6-12-13-14-15	1-3-12-13-14-15	5
14	1-2-3-4-7-8-10-11-12-13-14-15	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15	1-2-3-4-7-8-11-12-13-14-15	1

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15	1-2-3-4-7-8-10-11-12-13-14-15	1-2-3-4-6-12-13-14-15	1-2-3-4-12-13-14-15	3

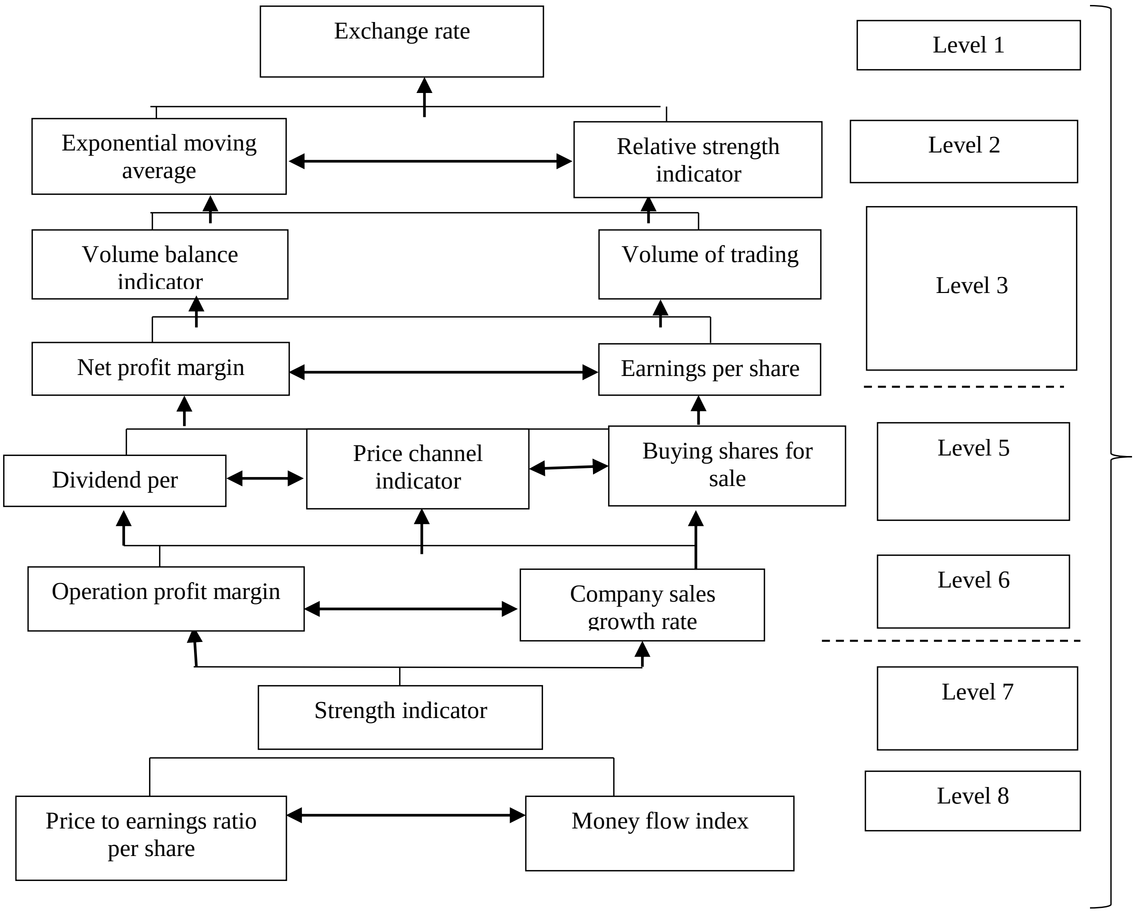

Fig. 2 Hierarchical model

The exchange rate index, which is positioned at the highest level, has the least impact and is classified as a dependent variable. However, the money flow index (MFI) and the price-to-earnings ratio (P/E), which are located at lower levels, are the most influential indicators with high driving power and have been identified as the most critical criteria for stock price prediction. Furthermore, the presence of eight levels in this table indicates that the model is divided into eight conceptual layers.

4 Conclusion and Recommendations

Both micro and macro variables have a direct and indirect impact on the stock market and, consequently, its price index. Any variable that affects the selection of asset portfolios by stock buyers can also affect the stock price index. On the other hand, since investing in the stock market is done through buying shares of existing companies in it, any factor that affects the value of these companies' stocks at the micro or macroeconomic level can also affect the stock market index. Predicting the trend of the stock market based on historical data is

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difficult due to the noisy and highly volatile environment. Stock price fluctuations are due to the information available in the market and market participants' actions based on this information. Information related to macroeconomic factors has a greater impact on stocks than information related to the industry sector. Both technical and macroeconomic variables are essential for predicting stock prices and consider different information. Economic macro models work better despite high volatility, while technical models work better when volatility is lower. Combining these two models provides a reliable prediction of volatility. Both micro and macroeconomic variables also play an important role in stock price volatility. Price increases and decreases may depend on various socio-economic factors such as market history, commodity prices, news, public sentiment, interest rates, foreign exchange rates, etc. Additionally, several financial factors affect stock performance, including profitability, debt repayment ability, management performance, management efficiency ability, financial structure ability, and non-financial factors. The literature provides many methods and techniques for predicting stock market behavior.

The aim of this research is to develop a comprehensive model for predicting stock prices in the stock market using a structural interpretive modeling approach and examining the relationships between them. Therefore, researchers in this study tried to identify and determine the hierarchy of predictive variables for stock prices by combining fuzzy Delphi and structural-interpretive modeling methods. The fuzzy Delphi method identified the most important variables from the perspective of stock market experts and university professors, while the ISM approach provided a hierarchical view of the most important variables. This is because investors need to consider important variables and sub-variables and make informed decisions based on them. In order to answer the research questions, 54 variables were identified from research literature and were divided into four categories: technical, fundamental, behavioral, and macroeconomic. In two stages, 15 sub-variables were approved as final variables using the fuzzy Delphi method. The structural interpretive modeling approach (ISM) was used to develop a hierarchical relationship between these variables. The price-to-earnings ratio, which is an old and widely used tool for valuing stocks and indicates that the price of a company's stock is several times the amount of cash earnings that the company allocates to each share or the price of the stock relative to the earnings that the stock exchange company distributes to its shareholders, is one of the important financial factors affecting stock performance. Attention to this ratio is always considered by shareholders when buying and selling stocks in stock companies. The money flow index also affects stock prices because increasing liquidity disrupts the real balance of money. But since people tend to maintain their real balance, they try to push the extra money towards buying other financial assets, including stocks. Therefore, increasing the volume of money leads to an increase in demand and consequently an increase in stock prices. Other important variables have also been identified in predicting stock prices as pricing products in stock companies are done in various ways and are an important item. For investing in stocks In the ISM model, it is observed that the price-to-earnings ratio and money flow index are at the end of the hierarchy (level 8), which has a high driving force. The variables that are at the bottom of the hierarchy include exchange rate, relative strength index, and exponential moving average, which are the most susceptible indicators. Macroeconomic variables such as inflation rate, money growth rate, and exchange rate can affect stock returns. This is because individuals hold various combinations of cash, stocks, bank deposits, equity securities, gold, and currency in their financial asset portfolios. Additionally, these variables have an impact on the financial conditions of economic firms and the value of their stocks. Changes in the volume of money, exchange rates, inflation rates, and bank interest rates affect individuals' demand for holding

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each of these assets, including stocks, which in turn affects stock market indicators. It is believed that stock prices are determined by some fundamental macroeconomic variables such as inflation rate, exchange rate, interest rate, and money supply volume. Level 5 includes buying and selling stocks, price channel indicator, and earnings per share. These criteria, which are a combination of technical and fundamental dimensions, are important for predicting stock prices as they undergo changes in both dimensions and can be predicted using trading volume indicators and indicators created by individuals, which are level 3 criteria. These are intermediate-level criteria that act as a link for the entire system and generally have high penetration and dependence power. Level 1 criteria are considered highly dependent factors, including macroeconomic components and relative strength index and exponential moving average indicators. Therefore, in order to predict stock prices, technical variables in the short term and fundamental variables in the long term, as well as a combination of both in the medium term, are of great importance. In the course of the study conducted on stock market forecasters, it is suggested that they use the criteria extracted in this research to predict stock prices, as these criteria are based on the opinions of experts and market investors. It is also recommended for future research to test the generalizability of the results of this study by surveying other experts, as well as using other methods in fuzzy conditions to obtain the most important criteria for predicting stock prices and comparing and analyzing the results with those of the present study, or using a combination of several methods to identify and rank prediction criteria

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