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Developing and Validating a Model for Stock Portfolio Selection in the Iranian Capital Market

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Abstract

In the Iranian capital market, stock portfolio selection is a significant challenge for investors due to high volatility and the lack of reliable and effective models. The need for a valid model that considers both risk and return simultaneously is essential to improve investment decision-making and enhance market efficiency. Therefore, this study aims to develop and validate a stock portfolio selection model for the Iranian capital market. The research method is applied in nature and is descriptive in terms of data collection, using a survey-based approach. Initially, relevant studies and research on the subject are reviewed, followed by the development of the model based on field studies. After constructing the research paradigm, the model was formulated using statistical techniques such as Structural-Interpretive Modeling, and model fitting was carried out using the Least Squares method with Smart PLS software. Overall, the research model demonstrated that stock portfolio selection in the Iranian capital market leads to outcomes such as increased returns, risk management, capital preservation, encouragement of investment, market efficiency, and economic growth and development. The results of the analyses showed that the obtained model had acceptable validity (AVE≥0.5), reliability (CR≥0.7), and fit (GOF≥0.36).

Keywords: Stock Portfolio Selection, Capital Market, Structural-Interpretive Modeling.

1- Introduction

The selection of an appropriate investment portfolio in the stock market has always been a major focus for investors. The current economic conditions, including international sanctions and the dominance of a state-controlled economy, have created an environment of uncertainty regarding investment in the Tehran Stock Exchange. This uncertainty has led investors to face doubts about buying, selling, and holding stocks, prompting researchers to consider how to identify the most effective model for selecting a suitable stock portfolio in this uncertain market. Therefore, decision-making regarding the formation and selection of stock portfolios in recent years has led experts and market leaders, including fund managers, portfolio managers, and financial researchers, to propose various models. This issue remains a key concern in

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financial markets, with ongoing efforts to develop a more suitable model that avoids the shortcomings of previous ones (Nozari & Edalatpanah, 2023).

In fact, the question that preoccupies investors' minds is: aside from return and risk criteria, what other factors and criteria should be considered in stock portfolio selection, especially given the specific conditions of Iran? Stock markets are influenced not only by macroeconomic factors but also by thousands of other factors. The large number and the unknown nature of the factors affecting stock prices, combined with the complex relationship between these factors and stock prices, contribute to the uncertainty in investment decisions. One of the key tools to reduce this uncertainty, and a major topic in stock market investment, is the selection of an optimal stock portfolio (Fried et al., 2021). Consequently, investors strive to create a portfolio of the best stock picks by combining investments and continuously evaluating the performance of companies (Hoffart et al, 2021).

Today, the capital market is considered a major source of financing for companies, and if an appropriate model for portfolio selection is designed, taking into account the varying preferences of investors, it can direct available capital towards this market, thereby supporting domestic production in the country (Fahimi & Shahbandarzadeh, 2021). In capital markets, investors aim to optimize returns and reduce risks through optimal stock portfolio selection. Stock portfolio selection is directly affected by various factors, including economic conditions, market volatility, and management strategies. With the advancement of machine learning algorithms and new optimization methods, developing more accurate models for portfolio selection has become essential (Fleschacker et al., 2019; Surti et al, 2023).

On the other hand, the Iranian capital market is particularly complex due to severe economic volatility and international uncertainties (Navarro et al., 2023). The lack of a comprehensive model that simultaneously considers the diverse market conditions and investor preferences has created a gap in existing research (Vásquez et al., 2023). In this regard, the need for research focused on developing a dynamic model that can align investment strategies with market trends is evident (Aher et al., 2023). While extensive studies on portfolio optimization have been conducted in recent decades, many of these studies have either focused on data from developed markets or employed traditional and static techniques. For example, ARCH and GARCH models have been used to predict volatility in indices, but these models alone are not sufficient for aligning investment strategies with market changes (Li et al., 2022; Nozari & Abdi, 2024).

Moreover, in the Iranian capital market, there has been little attention to combining artificial intelligence techniques with economic and financial indicators. A major gap in current research is that most of it focuses on predicting returns, with little attention to addressing the decision-making needs of investors under different market conditions (Ashrafzadeh et al., 2023). However, designing an adaptive and multi-criteria model can help investors navigate various market conditions. Optimal stock portfolio selection not only increases investors' profitability but also enhances overall market efficiency (Hedayat et al., 2023). Given the development of modern financial tools and the complexities of the Iranian market, the importance of creating intelligent models capable of adapting to rapid market changes becomes even more significant (Solano et al., 2022).

This research could assist investors and financial managers in making smarter decisions in uncertain conditions. Additionally, the findings of this study could contribute to the development of new investment tools and the improvement of financial policies in Iran. By leveraging advanced algorithms and integrating financial data with macroeconomic indicators, more dynamic and adaptive portfolios can be created, reducing investment risk (Sinaga et al., 2022; Coelhoso et al., 2022).

2- Literature Review

Modern Portfolio Theory

Portfolio management is one of the most important branches of finance, aiming to determine an optimal combination of assets to maximize returns and minimize risk. The concept of portfolio optimization began with Markowitz's theory in the 1950s and was later expanded by models such as the Capital Asset Pricing Model (CAPM) and multifactor models like the Fama-French three-factor model and the Carhart four-factor model (Fama & French, 2015). These models have been updated to incorporate various factors such as liquidity, company size, and momentum in stock selection. Over time, more diverse criteria have been added to the analysis of investment portfolios (Feng et al., 2020).

Criteria for Stock Portfolio Selection

Stock portfolio selection in complex financial markets depends on a variety of factors. These factors include expected return, risk, liquidity, market volatility, and the correlation between assets. In recent years, other factors such as sustainability indices and ESG (Environmental, Social, and Governance) factors have been considered important in stock portfolio selection (Friede et al., 2015). Research has shown that in emerging markets like Iran, factors such as liquidity and systematic risk are particularly important due to the lower levels of market transparency and the various risk factors influencing these markets (Ghasemi et al., 2022).

Investor Behavior Analysis

Investor behavior is a crucial factor in stock portfolio selection. In modern behavioral finance theories, it is assumed that investors do not always act rationally and are influenced by factors such as risk appetite, overconfidence, and social influences. These factors can alter investment decisions and lead to price deviations in the market (Baker et al., 2019). In Iran, studies have shown that investors tend to follow market trends and collective decisions, which can influence the composition and selection of their portfolios (Karimi et al., 2021).

Impact of Systematic and Unsystematic Risks

Systematic and unsystematic risks are fundamental factors to consider in stock portfolio selection. In financial markets, systematic risk arises from factors such as economic fluctuations, government policies, and changes in interest rates, which affect the entire market. On the other hand, unsystematic risk is related to the specific characteristics of a particular company or industry (Hou et al., 2020). In the Iranian capital market, studies have indicated that systematic risks such as exchange rate fluctuations and macroeconomic policies can significantly impact portfolio performance and should be incorporated into portfolio selection models (Yazdani & Shariati, 2022).

Importance of Asset Correlation

Another key aspect of portfolio management is the consideration of correlations between the assets in the portfolio. In modern models, this correlation plays a critical role in reducing risk, as combining assets with negative or low correlation can help reduce portfolio volatility. Recent studies emphasize the importance of asset correlation in emerging markets due to the rapid changes and instability of these markets. Proper attention to asset correlation can assist investors in creating a more optimal combination of assets (Ilmanen et al., 2021; Fallah & Nozari, 2021; Kalogeras, 2017).

Studies on Factors Affecting Stock Portfolio Selection

Several studies have examined the factors influencing stock portfolio selection. In the following, we will review some of these studies:

Table 1: Research Background

Authors and Year	Topic	Methods and Tools	Results
Taghizadeh et al. (2022)	Evaluation of Optimal Portfolio with Market Criteria	Multicriteria Decision-Making, Data-Based	Identification of factors affecting the portfolio, including country and systematic risk
Taghizadeh et al. (2021)	Evaluation of Optimal Portfolio with Accounting Criteria	AHP and Multicriteria Decision-Making	Unsystematic risks and financial obligations are influential
Asiabi Aghdam et al. (2018)	Impact of Behavioral Economics on Stock Portfolio	Behavioral Analysis	Loss aversion and conservatism affect decision-making
Raei et al. (2021)	Performance Assessment of Portfolio with ELECTRE Model	ELECTRE and Model Ranking	Superiority of 1/N and minimum variance models
Fried et al. (2021)	Stock Portfolio Selection with Fuzzy Preference Approach	Fuzzy Preferences	Profitability and efficiency are the most important criteria
Yazdani Khodashahri et al. (2021)	Stock Price Prediction with Artificial Intelligence Algorithms	Neural Networks and Genetic Algorithm	High accuracy in predicting fluctuations with the proposed method
Mostafai and Daei (2009)	Multi-objective Stochastic Optimization of Stock Portfolio	Grey Wolf Algorithm	The Grey Wolf algorithm outperforms Genetic Algorithm
Shams Lahroudi et al. (2018)	Optimal Portfolio Selection with Fuzzy MCDM	Fuzzy Hierarchical Analysis	Weighting of criteria based on expert opinions
Lou, Faff, and As (2016) Kalogeras (2019)	Improving Mean-Variance Model with Asymmetric Distribution	Multivariate Probability Model Sampling	Reduction of estimation error with the marginal model
Zimi et al. (2018)	Portfolio Optimization Model with Variance and Skewness	Two-stage Algorithm	Offering a portfolio with lower risk and higher return
Plachel (2019)	Stable Portfolio Optimization with Systematic Model	Correlation Matrix	Model improvement by combining expectations of systematic risk
Rosadi et al. (2020)	Stable Covariance Model for Mean-Variance	Stable Matrix Estimator	Better performance with outlier data
Ruchika and Aparna (2020)	Portfolio Optimization with Stochastic Dominance Constraints	Sharpe Ratio, Star, and Standard Deviation	Improved portfolio performance with stochastic dominance

3- Research Methodology

This research utilizes a combination of Interpretive Structural Modeling (ISM) and Structural Equation Modeling (SEM) to analyze the factors influencing stock portfolio selection in the Iranian capital market. Each of these methods has different applications in the research process:

1. Interpretive Structural Modeling (ISM)

- Objective: To identify and structure the relationships between variables or indicators.
- Application: In this research, ISM is used for qualitative analysis and identifying the relationships between key indicators affecting stock portfolio selection. This method allows researchers to identify key factors and display their interrelationships in a hierarchical model.
- Process: Initially, variables are identified through expert interviews or qualitative questionnaires, and then a structural access matrix is created to analyze the relationships between the variables.

2. Structural Equation Modeling (SEM)

- Objective: To test and explain hypothetical models using empirical data.
- Application: In this research, after determining the initial model structure through ISM, SEM is used for more detailed analysis and testing the relationships between independent and dependent variables. This method allows for the simultaneous examination of multiple relationships among latent and observed variables.
- Tool: Smart PLS software is used for analyzing the structural equation modeling data. SEM is particularly useful when we need to evaluate the overall model fit and respond to statistical hypotheses.

Data Collection Method

1. Qualitative Data:

- To identify initial factors and relationships, semi-structured interviews with financial experts and investment managers are used. This information serves as input for the ISM model.
- Sampling Method: Purposeful or snowball sampling is used to access specialists with in-depth knowledge in the capital market field.

2. Quantitative Data:

- For running the SEM, standardized questionnaires are used, which are designed based on the variables and relationships identified in the first phase.
- Data Collection: Data is collected from investors, portfolio managers, and companies active in the Tehran Stock Exchange.
- Sampling Method: Stratified random sampling is employed to ensure appropriate representation from different groups.

3. Measurement Tools:

- Questionnaires are designed using five-point or seven-point Likert scales to measure respondents' opinions on the research variables.

4- Research Findings

Qualitative Section

In the qualitative section, through three stages using the Delphi method, the dimensions and components of the research were confirmed, and a researcher-made questionnaire was developed and its validity was confirmed. In the first stage of the Delphi process, a checklist containing 5 dimensions and 26 components proposed by the researchers for designing the model was provided to the expert group to obtain their opinions regarding the importance of including these dimensions and components in the model and the questionnaire. The experts were asked to indicate their agreement or disagreement with the inclusion of these dimensions and components in the research model. As shown in Table 2, at this stage, all dimensions and components were confirmed and entered into the second stage of the Delphi process.

Table 2: The level of agreement of experts with each of the components and indicators

Component	Dimension	Agree Frequency	Agree Percentage	Disagree Frequency	Disagree Percentage	Mean	Standard Deviation	Result
Causal Conditions	Fundamental	23	92%	2	8%	4.24	0.83	Accepted
	Industrial	25	100%	0	0%	3.92	0.9	Accepted
	Market	22	88%	3	12%	4.04	0.84	Accepted
	Economy	22	88%	3	12%	3.88	0.83	Accepted
	Stock Market Participants' Behavior	22	88%	3	12%	3.6	0.7	Accepted
Contextual Conditions	Capital Market Structure	25	100%	0	0%	3.84	0.8	Accepted
	Legal and Governance Environment	20	80%	5	20%	3.8	0.86	Accepted
	Investment Culture	22	88%	3	12%	3.88	0.72	Accepted
	Information Technology	23	92%	2	8%	3.92	0.9	Accepted
Facilitators	Investor Characteristics and Preferences	20	80%	5	20%	3	1.5	Accepted
	Market Limitations	23	92%	2	8%	2.88	1.45	Accepted
	Parallel Markets	23	92%	2	8%	3.24	1.12	Accepted
	Support and Facilitation Factors	25	100%	0	0%	3.48	1.5	Accepted
Outcomes	Return Increase	21	84%	4	16%	2.8	1.38	Accepted
	Risk Management	20	80%	5	20%	3.16	1.54	Accepted
	Capital Preservation	25	100%	0	0%	3.4	1.41	Accepted
	Investment Encouragement	20	80%	5	20%	3.68	1.43	Accepted
	Capital Market Efficiency	22	88%	3	12%	3.68	1.24	Accepted
	National Economic Growth & Development	23	92%	2	8%	3.44	1.41	Accepted
Strategies	Asset Diversification	22	88%	3	12%	3.32	1.37	Accepted
	Identifying Investment Opportunities	20	80%	5	20%	3.4	1.11	Accepted
	Capital Management	21	79%	3	15%	2.88	1.67	Accepted
	Trading Strategy Determination	25	100%	0	0%	3.68	1.1	Accepted

Next, the structural-interpretive modeling is presented in order to develop the proposed paradigm model.

Structural-Interpretive Modeling (ISM)

To start, a 4x4 matrix of indicators was developed to form the structural interaction matrix. This matrix was provided to the managers, who completed it according to the following principles:

- **V**: Variable iii helps in achieving variable jjj.
- **A**: Variable jjj is improved only by variable iii.
- **X**: Variables iii and jjj help each other in achieving their goals.
- **O**: Variables iii and jjj are not related.

Based on the entries in the SSIM (Structural Self-Interaction Matrix):

- If (i,j)(i, j)(i,j) is marked as **V** in the SSIM, then in the reachability matrix, (i,j)(i, j)(i,j) is set to 1 and (j,i)(j, i)(j,i) is set to 0.
- If (i,j)(i, j)(i,j) is marked as **A** in the SSIM, then in the reachability matrix, (i,j)(i, j)(i,j) is set to 0 and (j,i)(j, i)(j,i) is set to 1.
- If (i,j)(i, j)(i,j) is marked as **X**, then in the reachability matrix, both (i,j)(i, j)(i,j) and (j,i)(j, i)(j,i) are set to 1.
- If (i,j)(i, j)(i,j) is marked as **O**, then both (i,j)(i, j)(i,j) and (j,i)(j, i)(j,i) are set to 0.

The reachability matrix is constructed using the structural interaction matrix as outlined above. The matrix transformation follows the rules:

- For **V**: (i,j)=1(i, j) = 1(i,j)=1 and (j,i)=0(j, i) = 0(j,i)=0
- For **A**: (i,j)=0(i, j) = 0(i,j)=0 and (j,i)=1(j, i) = 1(j,i)=1
- For **X**: (i,j)=1(i, j) = 1(i,j)=1 and (j,i)=1(j, i) = 1(j,i)=1
- For **O**: (i,j)=0(i, j) = 0(i,j)=0 and (j,i)=0(j, i) = 0(j,i)=0

Using these relationships, the reachability matrix shown in Table (3) is created.

Table 3: Reachability Matrix

	A	B	C	D
A	1	1	0	0
B	0	1	1	1
C	0	1	1	1
D	1	0	1	1

With the reachability matrix obtained, two sets, namely the reachability set and the antecedent set, are defined to determine the criteria. The intersection of these sets is then computed. The reachability set is defined as the set where the row entries of the criteria are represented as one, and the antecedent set is defined as the set where the column entries of the criteria are represented as one. According to the transitivity property in mathematical logic, if (i,j)=1(i, j) = 1(i,j)=1 and (j,k)=1(j, k) = 1(j,k)=1, then (i,k)=1(i, k) = 1(i,k)=1. This means that criteria indirectly affect each other. The relationship between two variables that connect after applying this logic is represented as 1.

Table 4: Modified Reachability Matrix (Final Reachability Matrix)

	A	B	C	D
A	1	1	1	1
B	1	1	1	1
C	1	1	1	1
D	1	1	1	1

In Table 4, considering the transitivity relationship, if iii and jjj are related and kkk and jjj are related, then iii and kkk are also related. Consequently, some entries will be converted to 1. Additionally, the matrix is divided into various levels using the following method to determine the reachability and antecedent sets for each criterion. The reachability set is defined as the set where the row entries of the criteria are represented as one, while the antecedent set is the set where the column entries of the criteria are represented as one. By obtaining the intersection of these two sets, the next column of the table (Intersection) will be completed. The first row where the intersection of the two sets equals the reachability set will determine the first priority level.

Based on the evaluations conducted in the table and figures above, and using the prioritized levels of criteria and the reachability matrix, the final matrix of driving power and dependence is constructed. In this matrix, the largest number is assigned the highest rank, and the smallest number is assigned the lowest rank. The final reachability matrix must be categorized into different levels. For determining the level of variables in the final model, three sets—output, input, and intersection—are formed for each variable. In the first table, variables whose intersection of output and input sets is identical are considered as common set variables in the hierarchical process, meaning these variables do not affect the creation of any other variables. After identifying these variables, they are removed from the list of other variables. This process continues until all variables' levels are determined. In this study, six levels of variables were obtained in thirteen tables, and the final results are summarized in Table 3. Research indicators whose output and intersection sets are completely identical are placed at the highest level in the structural-interpretive model hierarchy.

The groups depicted are defined as follows:

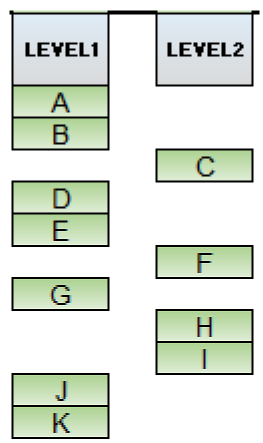
Group 1: Criteria that have weak power and weak dependence. These variables are almost independent from the system, as they have weak connections with it. In the sample examined, no variables fall into this group.

Group 2: Variables that have weak power but strong dependence.

Group 3: Variables that have both strong power and strong dependence.

Group 4: Variables that have strong power but weak dependence.

Table 5: First Stage of Level Determination in the ISM Hierarchy



In the last column, the levels are determined as follows: if the intersection of the achievable set and the prerequisite set with the achievable set is equal, the corresponding variable is placed at the highest level in the ISM matrix hierarchy. In the ISM graph, the interrelationships and influences between criteria, as well as the relationships between criteria at different levels, are visible, which helps in better understanding the decision-making space.

The groups in Figure (1) are defined as follows:

Group 1: Criteria with weak power and weak dependence. These variables are almost separate from the system because they have weak connections to the system. In the sample under review, no variable falls into this group.

Group 2: Variables with weak power but strong dependence.

Group 3: Variables with strong power and strong dependence.

Group 4: Variables with strong power but weak dependence.

Table 6: Stage of determining levels in the ISM hierarchy.

	Driving forces	Dependent forces
A	17	17
B	18	17
C	17	16
D	17	16
E	16	16
F	18	15
G	17	16
H	18	15
I	18	16
J	18	16
K	12	18

In the last column, the levels are determined as follows: if the intersection of the achievable set and the prerequisite set with the achievable set is equal, the corresponding variable is placed at the highest level in the ISM matrix hierarchy. In the ISM graph, the interrelationships and influences between criteria, as well as the relationships between criteria at different levels, are revealed, which helps in better understanding the decision-making space. The results of the variable level classification are shown in the diagram below:

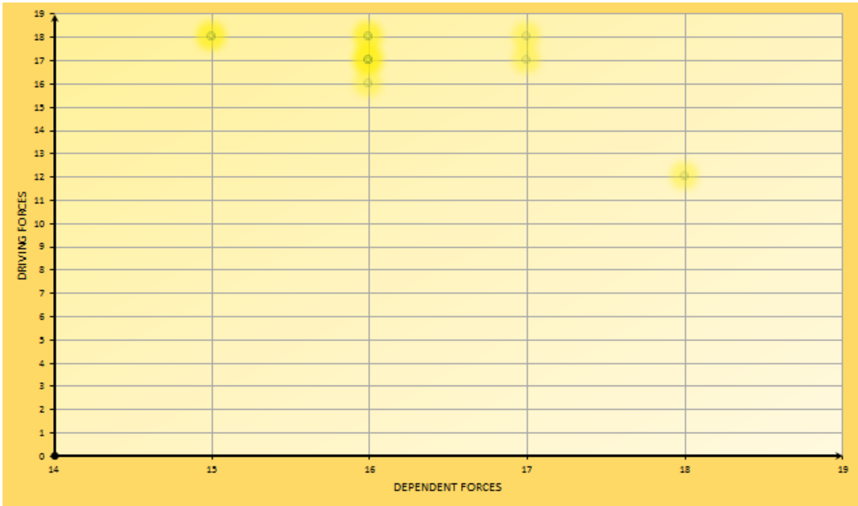


Figure 1: MICMAC Diagram

The results of the variable level classification are presented in the following section under structural equation modeling.

Testing the Model Using Structured Linear Relationships

At this stage, in order to evaluate the conceptual model of the research and also to determine the existence or non-existence of causal relationships between the research variables and to examine the fit of the observed data with the conceptual model, the research hypotheses were tested using structural equation modeling. The results of the model test are reflected in the diagram.

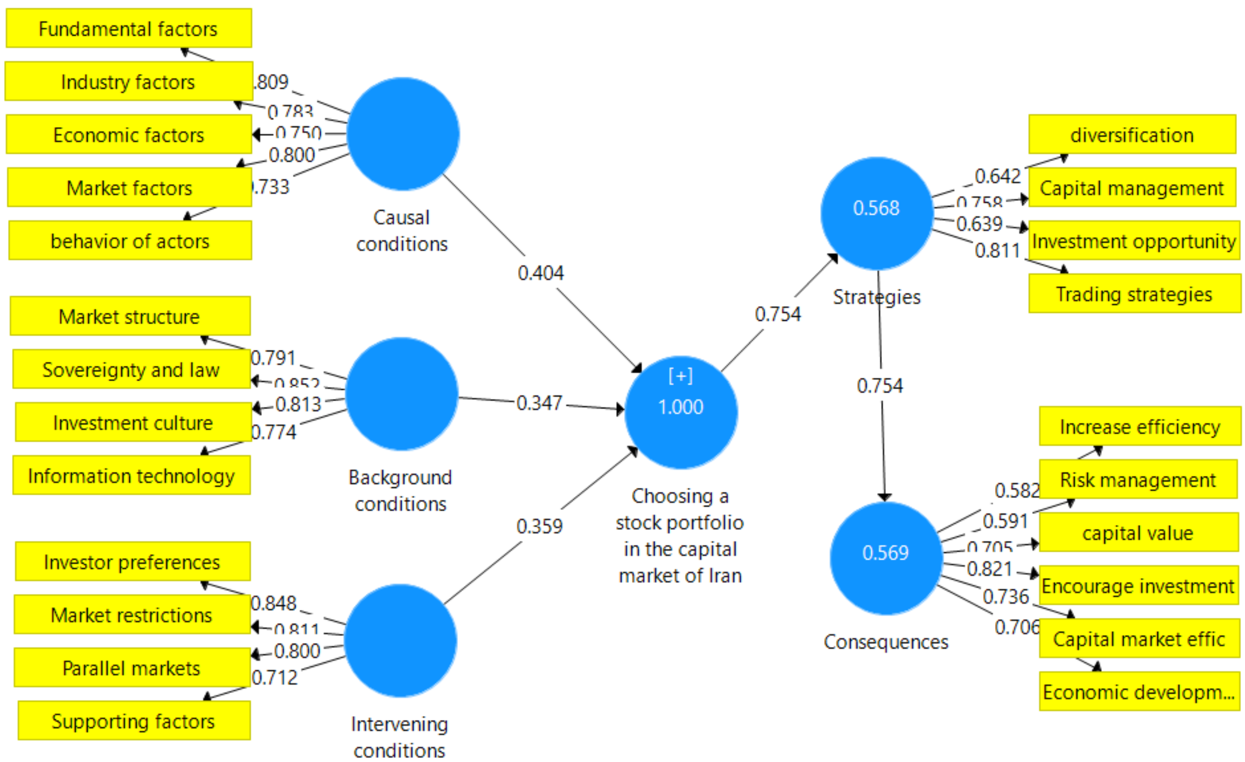


Figure 2: Measurement of the Overall Model in Standard Mode

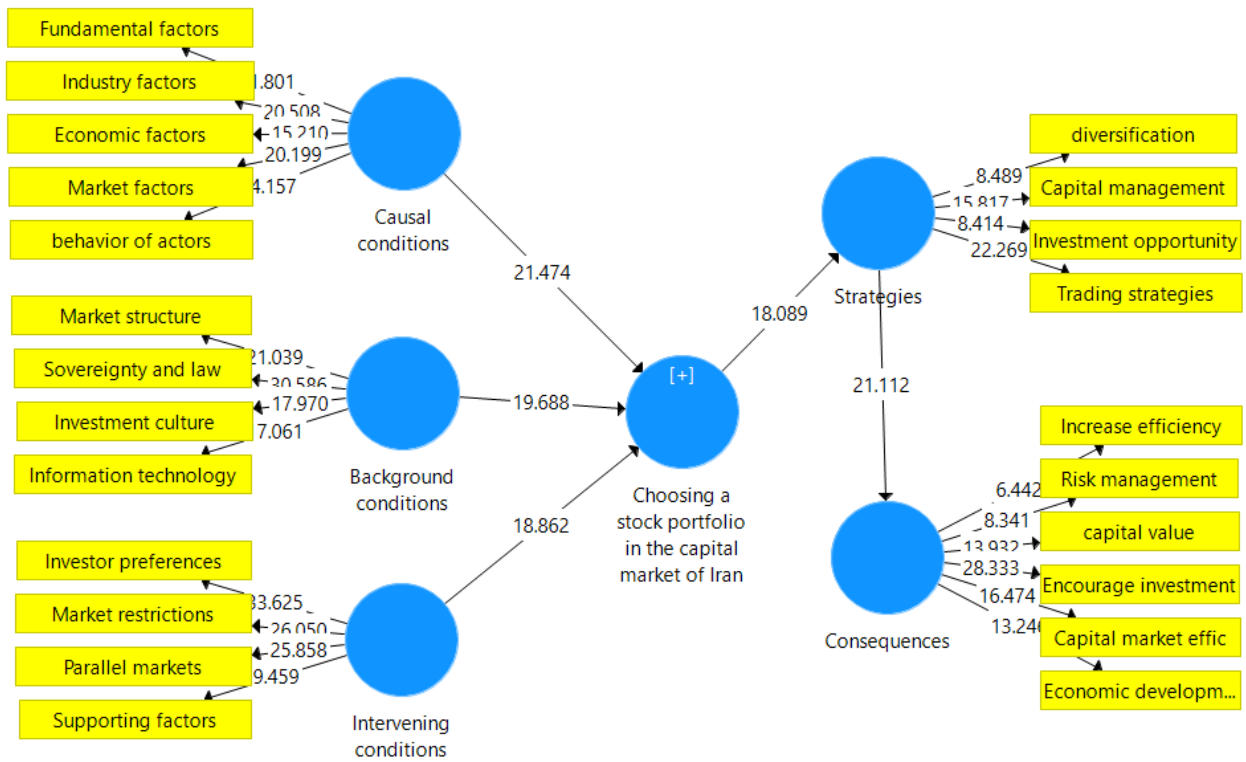


Figure 3: Measurement of the Overall Model in Significant Mode

Cronbach's alpha and composite reliability were used to assess reliability, while convergent validity was employed to assess validity. The GOF (Goodness of Fit) index was used to evaluate the model fit.

Table 7: Reliability and Validity of the Outer Models

Variable	**CR**	**AVE**	**MSV**	**Fornell and Larcker Matrix**				
				1	**2**	**3**	**4**	**5**
Causal Conditions	0.787	0.552	0.193	0.743				
Contextual Conditions	0.844	0.644	0.478	0.342	0.803			
Intervening Conditions	0.918	0.651	0.423	0.331	0.47	0.807		
Strategies	0.885	0.72	0.478	0.44	0.692	0.65	0.849	
Outcomes	0.96	0.649	0.149	-0.066	-0.259	-0.213	-0.386	0.806

Reliability and Validity

- A Cronbach's alpha value higher than 0.70 indicates acceptable reliability.
- A CR value above 0.70 for each construct signifies adequate internal consistency for the measurement model.
- An AVE value greater than 0.50 indicates acceptable convergent validity.
- Considering the thresholds of 0.10, 0.25, and 0.36 for weak, moderate, and strong GOF (Goodness of Fit), a GOF value of 0.62 indicates a strong model fit.

5- Conclusion

The results of this research indicate that portfolio selection in Iran's capital market is influenced by a set of causal conditions categorized into five main groups. Fundamental company factors, including profitability, financial structure, growth, and stability of performance, directly impact the attractiveness of a company's stock, helping investors better assess growth potential and inherent risks. Additionally, industry conditions play a crucial role in investor decision-making. Factors such as industry competition, emerging technologies, and regulations affect company performance and stock appeal, and changes in these factors can rapidly shift industry dynamics, impacting investment returns.

Market-related factors—such as trends, price fluctuations, and stock liquidity—affect investor behavior in various ways, particularly in short-term decisions. In a dynamic, volatile market like Iran's, investors need to stay informed about real-time changes and manage risks stemming from these fluctuations. Economic conditions, including inflation rates, interest rates, monetary and fiscal policies, and political circumstances, significantly impact market returns and risks. Economic instability and sanctions can directly affect macroeconomic indicators, ultimately impacting the capital market, as addressed in this study. Behavioral finance factors highlight the role of cognitive biases and emotions in investment decisions. Emotional behaviors, such as excitement from price fluctuations or herd mentality, sometimes lead to irrational decisions. These findings underscore the importance of understanding investor psychology, in addition to financial analyses, for optimizing portfolio selection.

Overall, this research, using grounded theory, presents a comprehensive model for portfolio selection that can enhance investment decisions and risk management. The findings suggest that for success in Iran's capital market, a combination of fundamental analysis, understanding of market and industry conditions, macroeconomic risk management, and investor behavior awareness is essential. Due to Iran's highly dynamic market, it is recommended that investors employ adaptive models and continuously update their information and strategies.

The study shows that portfolio selection in Iran's capital market is also influenced by a set of contextual conditions divided into four main categories. These conditions provide a framework for investor decision-making and play a vital role in shaping investment strategies and risk management. Legal and governance frameworks, including regulations and supervisory policies set by the stock exchange organization and governing bodies, impact investor trust and participation in the market. Investor objectives and expectations also play a crucial role in portfolio selection. Some investors seek short-term profits, while others may pursue long-term goals, such as capital preservation or sustainable returns, resulting in diverse asset allocation and risk tolerance based on these expectations.

Investor constraints, such as available capital, time limitations, and risk tolerance thresholds, significantly impact portfolio formation. Investors with limited resources must carefully choose stocks, manage liquidity, and mitigate risk. Additionally, time constraints can shift investment strategies from long-term to short-term, requiring different risk management approaches. Personality traits, including risk tolerance, confidence, and decision-making style, influence portfolio selection. Overall, this research suggests that portfolio selection in Iran's capital market is not solely confined to financial factors; contextual conditions also play a crucial role in shaping investor strategies and decisions.

Furthermore, the study reveals that portfolio selection in Iran's capital market is influenced by intermediary conditions that act as facilitators or limitations in the decision-making process and investment strategy implementation, connecting various influential market variables. Preconditions, such as fundamental knowledge and information on financial analysis, risk assessment, and investment tools, are essential for informed decision-making and optimal portfolio management. Market conditions, including volatility, upward or downward trends, and other investors' behaviors, influence both short-term and long-term strategy adjustment. Parallel markets, such as gold, currency, and real estate, also affect investor decisions, as correlations among these markets sometimes lead investors to diversify across other markets for risk management.

Financial institutions and tools facilitate portfolio selection and management. Analytical skills, risk management, and market behavior understanding are essential for investors to make effective decisions during volatile conditions. Barriers such as lack of information transparency, political and economic risks, and weak financial infrastructure can hinder strategy implementation, reducing portfolio productivity. Identifying and managing these barriers is crucial.

The study's results show that a diverse and comprehensive approach is required for portfolio selection in Iran's capital market, divided into seven main strategy categories. These strategies help investors make better decisions and manage investment-related risks by understanding market conditions, economic factors, and behavioral factors. Fundamental strategies involve detailed analysis of company characteristics and performance. Industry-related strategies assess industry position and outlook, guiding investors to adjust their portfolios based on future potential and protect against industry-specific risks.

Market-related strategies involve analyzing overall market behavior, volatility, and price trends, enabling investors to respond to market movements. Behavioral finance strategies focus on investor behaviors. Recognizing behavioral biases helps investors avoid emotional decisions and make more rational ones. General portfolio selection strategies address investment goals, asset allocation, and risk management. With analytical tools and modern technology, investors can update and adjust their portfolios for optimal returns.

The study emphasizes the importance of a systematic approach in portfolio selection, supporting investors in Iran's capital market to improve performance. Each of these strategies alone is not sufficient; investors should consider all factors simultaneously to optimize their investment decisions.

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