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Designing a Stock Return Prediction Model Using Novel Composite Variables in the Tehran Stock Exchange with an Integrated DEMATEL and Interpretive Structural Modeling Approach

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A B S T R A C T

The purpose of this study was to design a model for predicting stock returns of companies using novel composite variables in the Tehran Stock Exchange. In terms of objective, this research is developmental–applied. The method used in this study is mixed, which includes the historical method (data collection) and the survey method (questionnaire distribution). Additionally, to collect and write the theoretical foundations of the research, articles, books, and reputable available sources were utilized. The statistical population and sample of this study consist of experts familiar with accounting and stock exchange concepts. The sampling method is purposive. The methods employed in this research are DEMATEL techniques and Interpretive Structural Modeling (ISM). The software used included EXCEL and MICMAC. Twelve indicators were identified. These indicators are: financial variables, macroeconomic variables, interest rate, cognitive biases, market sentiment, media news, artificial intelligence, trading algorithms, big data, corporate governance, market regulations, and financial transparency. The proposed model for predicting stock returns, based on novel composite variables in the Tehran Stock Exchange, with a comprehensive, integrative, and multilayered perspective, has succeeded in narrowing the gap between theory and market reality. Understanding the interaction between technology, investor psychology, institutional environment, and economic data has opened a new horizon in analyzing and predicting market behavior. Such a model not only has a high predictive capacity but also serves as a tool for deeper understanding of market dynamics, policymaking, designing innovative financial instruments, and enhancing market transparency. Therefore, this model is considered an effective step in the scientific development of Iran's capital market.

Keywords: *Stock return, composite variables, stock return prediction, stock exchange*

1. Introduction

Forecasting stock returns has long occupied a central place in financial economics because it underpins capital allocation, risk management, and the design of market-stabilizing policies. Yet the empirical record shows that return predictability is fragile, often episodic across regimes, and highly sensitive to modeling choices and information sets. Recent advances across three fronts—data availability, machine learning (ML), and decision-analytic modeling—create an opportunity to revisit the problem using broader, composite constructs that integrate financial, behavioral, technological, and institutional drivers. Building on this opportunity, the present study develops a multi-layered predictive framework for the Tehran Stock Exchange (TSE) that fuses novel composite variables with an integrated DEMATEL–ISM procedure to uncover causal structure and hierarchical salience before estimation. This design responds to mounting evidence that predictive relations vary with macro–financial cycles, crisis states, and market microstructure, and that combining signals across heterogeneous domains can raise both robustness and out-of-sample performance (Diebold & Shin, 2019; Vatsa et al., 2024; Y. Zhang et al., 2020).

A large literature demonstrates that “traditional” financial predictors—valuation ratios, profitability screens, and accrual-based diagnostics—retain explanatory content but are not uniformly reliable across states of the world. For example, research on the Piotroski F-score shows that accounting-based signals interact with business conditions, strengthening in some regimes and attenuating in others, which underscores the need for regime-aware modeling and richer covariate sets (Anderson et al., 2025). Calendar effects and payout announcement windows also introduce predictable variation in returns, revealing behavioral and institutional channels that any comprehensive predictive system should accommodate (Hasan & Al-Najjar, 2025). In parallel, the rapidly digitizing firm has altered information production and investor learning; evidence indicates that “new quality” productivity and digital transformation can buffer prices against shocks, reshaping crisis-time resilience and, by implication, the mapping from shocks to expected returns (Chen & Alexiou, 2025). For the TSE specifically, recent work has begun to articulate composite constructs tailored to local market features and data infrastructure, suggesting that a blended set of variables can capture the multi-cause nature of return formation more effectively than single-category predictors (Afshin Seyed Mohammad et al., 2025).

Macro–financial environments materially condition predictability. Stock market cycles co-evolve with macro dynamics, including growth, credit, and policy regimes, and return signals exhibit state dependence along these dimensions (Vatsa et al., 2024). Global risk spillovers, especially in segmented segments such as Islamic equities, propagate through multi-scale channels and can be isolated via time–frequency methods, reinforcing the argument for cross-domain composite variables that capture local and international risk drivers simultaneously (Kazak et al., 2024). Episodes such as the COVID-19 pandemic further demonstrate how exogenous health shocks reprice risk across both developed and emerging markets, amplifying volatility and disturbing standard signal-to-noise ratios; predictive models that ignore such structural breaks will likely underperform when they are most needed (Khan et al., 2024). These macro-systemic forces also interact with sentiment and information flows—from social media-mediated attention to news shocks—modulating the stochastic environment in which forecasts are made (de Sousa-Gabriel et al., 2024; Metiu et al., 2023).

Behavioral and sentiment dimensions have moved from peripheral to central in modern return forecasting. Investor sentiment, noise trading, and attention cycles not only move prices contemporaneously but also forecast short-horizon returns and volatility, often nonlinearly (Chen et al., 2022; Sakariyahu et al., 2024). Textual measures, including those extracted from news and social platforms, offer high-frequency, high-dimensional signals that require nonlinear learning to translate into forecasts; their usefulness has been documented in volatility prediction and broader market surveillance (Zhang et al., 2021). The broader review literature confirms that sentiment-aware ML and deep learning architectures materially improve nowcasting and short-term forecasting performance across markets and horizons, albeit with important implementation caveats around overfitting and regime drift (Sonkavde et al., 2023). Within a composite-variable strategy, these behavioral inputs are essential complements to fundamentals and policy metrics.

On the modeling side, a wave of ML and statistical learning methods—ranging from regularized forecast combination to deep neural networks and online sequential extreme learning machines—has expanded the toolkit for mapping complex, nonlinear relations between predictors and returns (Das et al., 2021; Diebold & Shin, 2019; Samal

& Dash, 2023; Shen & Shafiq, 2020). Comparative studies at high frequency show that method choice and sampling design crucially affect realized performance, with different algorithms excelling under different data-generating processes (Akyildirim et al., 2022). Hybrid procedures that combine signal engineering (e.g., variational mode decomposition) with sequence models (e.g., LSTM) have yielded accuracy gains in emerging-market contexts and are particularly relevant for markets with episodic illiquidity and structural shifts (Haghighi Naeini et al., 2023; Najarzadeh et al., 2020). The broader evidence base indicates that extreme learning machines, often meta-heuristically optimized, can deliver competitive error metrics for price and volatility forecasting, adding to the case for flexible learners downstream of a careful variable-engineering stage (Das et al., 2022).

Risk and uncertainty indices offer another indispensable layer in composite design. Economic policy uncertainty (EPU) measures, both global and local, affect discount rates, cash-flow expectations, and hence volatility, with forecasting frameworks such as GARCH-MIDAS showing that macro-uncertainty can improve conditional variance forecasts for energy and carbon markets as well as equities (Huang & Luk, 2020; Liu et al., 2021). Cross-asset signals like VIX and EPU competed as pandemic-time predictors, highlighting that which signal dominates is state-contingent—a direct motivation for multi-source composites and forecast combination (Wang et al., 2020). Beyond policy uncertainty, implied volatility and dimensionality-reduced uncertainty composites have repeatedly demonstrated incremental predictive power for realized volatility, reinforcing the value of information compression techniques when working with large, correlated indicator sets (Liang et al., 2020; Yan et al., 2022). Parallel studies document that uncertainty indices themselves can drive higher-moment dynamics in returns, affecting tail risk and correlation structures (Gong et al., 2022; H. Zhang et al., 2020).

International evidence on return and volatility prediction also cautions that parameter instability and model uncertainty are ubiquitous; robust strategies thus rely on procedures that adapt weights and structures through time, or that explicitly ensemble across specifications to hedge model risk (Kyriakou et al., 2020; Y. Zhang et al., 2020). In that spirit, statistical learning approaches to stock selection and excess-return forecasting in large cross-sections have emphasized feature selection, shrinkage, and nonparametric regression, often outperforming linear benchmarks and underscoring the benefit of diversified, regularized predictors (Cheng et al., 2019; Wu et al., 2020). Reviews of anomalies through the ML lens likewise find that many cross-sectional "effects" are fragile out of sample unless systematically combined and regularized, again pointing to composite constructs and disciplined aggregation (Azevedo et al., 2023).

For the Iranian context, the need for composite, multi-domain predictors is amplified by market microstructure characteristics, liquidity patterns, and the interaction between domestic macro policy and global shocks. Studies on the TSE have explored dynamic return modeling, volatility forecasting with quantum-inspired or MIDAS formulations, and hybrid deep-learning forecasters, providing strong empirical motivation for the careful design and testing of locally calibrated predictors and architectures (Amini Mehr et al., 2021; Manjazeb et al., 2023; Moradi et al., 2022; Nasiri et al., 2023; Rostami et al., 2023). Iranian research has also examined distributional assumptions and mixture-based methods for return modeling, which connect naturally to the tail-risk orientation in extreme value theory and the broader risk-measurement literature relevant to emerging markets (Melina et al., 2023; Zeinali & Yazdanian, 2021). Together, these streams suggest that a TSE-specific framework should: (i) integrate firm-level, behavioral, macro-policy, and market-microstructure variables; (ii) impose a causal/structural lens to clarify which drivers are upstream versus downstream; and (iii) implement flexible learning for estimation while controlling for overfitting and regime shifts.

The composite-variable taxonomy we adopt reflects this synthesis. Alongside standard financials, we incorporate macroeconomic aggregates and interest-rate proxies to represent discount-rate channels (Vatsa et al., 2024). We explicitly add behavioral blocks—investor attention, textual sentiment, and media news shocks—motivated by international evidence on attention-return links and nonlinear sentiment–volatility dynamics (Chen et al., 2022; de Sousa-Gabriel et al., 2024; Sakariyahu et al., 2024; Zhang et al., 2021). We include uncertainty and risk indices (policy and market based), given their documented forecasting value during turbulence and calm alike (Gong et al., 2022; Huang & Luk, 2020; Liang et al., 2020; Wang et al., 2020; Yan et al., 2022). We further incorporate technology-mediated factors—AI adoption and algorithmic-trading intensity—as both drivers of price discovery and modulators of microstructure noise, in line with high-frequency forecasting comparisons and statistical learning evidence (Akyildirim et al., 2022; Wu et al., 2020). Corporate governance, market regulation, and financial transparency enter as institutional quality levers that shape information asymmetry, trading frictions, and ultimately the mapping from information to price (Afshin Seyed Mohammad et al., 2025; Azevedo et al., 2023). Finally, we allow for tail-risk features and memory effects, given the stylized facts of financial returns; EVT-informed perspectives and fractional-dynamics models argue for accommodations to heavy tails and long memory in both design and evaluation (Melina et al., 2023; Tarasov, 2020).

Before estimation, we identify causal influence and hierarchical structure among these composites using DEMATEL and ISM. This step is nontrivial: if variables occupy different tiers in a causal hierarchy, then stacking them indiscriminately into a learner may obscure signal, induce leakage, or over-represent proximate effects relative to root causes. DEMATEL's total-relation matrix and MICMAC analysis separate net "drivers" from "dependents," while ISM maps levels and clarifies pathways, enabling targeted feature engineering and informed weighting of predictors (Samal & Dash, 2023). This structure-first approach is consistent with the broader insight that forecast combination benefits from prior organization of the information set—e.g., via regularized aggregation or hierarchical selection—especially under model uncertainty and parameter drift (Diebold & Shin, 2019; Y. Zhang et al., 2020). In downstream estimation, flexible learners such as deep networks, extreme learning machines, and hybrid VMD–LSTM systems can then be tuned to the structured composite inputs, acknowledging nonlinearity, regime switching, and heteroskedasticity (Das et al., 2022; Haghighi Naeini et al., 2023; Shen & Shafiq, 2020).

Volatility and correlation forecasting are treated as co-equal objectives, because predictive mean models often perform better when paired with credible conditional variance and co-movement estimates. International work on global equity volatility, implied-versus-realized dynamics, and uncertainty-conditioned variance models demonstrates material improvements from incorporating macro-uncertainty and option-implied information (Liang et al., 2020; Liu et al., 2021; H. Zhang et al., 2020). In addition, long-horizon excess-return forecasting and nonparametric predictive regressions encourage models that remain agnostic about functional form and accommodate slow-moving components—features we build into the design and validation protocol (Cheng et al., 2019; Kyriakou et al., 2020). From an operations standpoint, on-line and real-time forecasting procedures for related energy and commodity series emphasize pipeline efficiency and adaptive updating—considerations that inform our implementation plan for TSE equities in high-frequency or rapidly changing regimes (Zhao et al., 2021). The aim of this study is to design and validate a comprehensive predictive model for stock returns in the Tehran Stock Exchange by integrating novel composite variables with DEMATEL–ISM structural analysis and advanced machine learning techniques to enhance both accuracy and interpretability.

2. Methods and Materials

This study, in terms of objective, falls under developmental–applied research since its primary focus is on designing a conceptual model of company stock returns using novel composite variables in the Tehran Stock Exchange. The present research seeks to provide an innovative model by integrating theoretical knowledge and multi-criteria decision-making analytical methods—one that is scientifically rich and practically applicable in organizations and financial institutions. Because the study aims to offer a solution for improving managerial decision-making in the field of company stock returns using novel composite variables in the Tehran Stock Exchange, it is also categorized as applied research.

From a methodological standpoint, this research was conducted using a mixed approach comprising two main stages. In the first stage, a historical–library method was used to identify the components and dimensions of the model. In this part, the researcher, by utilizing valid scientific sources such as peer-reviewed articles, specialized books, and reports published by international academic institutions, collected theoretical information and extracted preliminary components. In the second stage, the research entered the survey phase, which, through specialized questionnaires and the Delphi technique, carried out the screening, validation, and analysis of relationships among the components.

The statistical population of the research consists of experts familiar with accounting and stock exchange concepts. Sampling was conducted purposively and judgmentally, considering the experience, expertise, and accessibility of the experts. In total, 12 qualified specialists were selected as the final sample for conducting the Delphi, DEMATEL, and Interpretive Structural Modeling (ISM) techniques. The main criterion for selecting these individuals was having either academic or executive experience in fields related to the research subject. Two main techniques were used for data analysis: the DEMATEL technique to determine causal and influential relationships among the components, and the Interpretive Structural Modeling technique to explain the levels and hierarchical structure of the components in the final model. These two methods were integrated to analyze both the interactions among variables and their hierarchy. Excel and MICMAC software were used as computational tools for data analysis and for mapping structural relationships.

3. Findings and Results

This study was conducted based on the viewpoints of 12 experts familiar with accounting and stock exchange concepts. Ultimately, 5 participants had 10 to 15 years of work experience, and 7 had more than 15 years of experience, as shown in Table 1 by frequency distribution.

Table 1

Demographic Characteristics of Experts

Demographic Characteristics	Frequency	Percentage
Gender – Male	8	66%
Gender – Female	4	34%
Work Experience – 10 to 15 years	5	42%
Work Experience – More than 15 years	7	58%
Education – Master's degree	6	50%
Education – Doctorate	6	50%
Total	12	100%

In this study, through a review of the research literature, a total of 12 main components were identified. Subsequently, in order to ensure the validity and reliability of the identified dimensions and components, and to verify their authenticity while addressing the research questions, the Delphi technique was employed. The Delphi method was carried out as follows.

Table 2

Delphi Analysis of Identified Components

Components	Code	Mean	Median	Mode	Std. Deviation	Range	Q1	Q2	Q3	Status
Financial Variables	C01	3.7	4	4	0.470	1	3	4	4	Confirmed
Macroeconomic Variables	C02	3.1	3	3	0.307	1	3	3	3	Confirmed
Interest Rate	C03	3.25	3	3	0.444	1	3	3	3.75	Confirmed
Cognitive Biases	C04	3.05	3	3	0.223	1	3	3	3	Confirmed
Market Sentiment	C05	3.3	3	3	0.470	1	3	3	4	Confirmed
Media News	C06	3.15	3	3	0.365	1	3	3	3	Confirmed
Artificial Intelligence	C07	3.35	3	3	0.434	1	3	3	4	Confirmed
Trading Algorithms	C08	3.45	3	3	0.510	1	3	3	4	Confirmed
Big Data	C09	3.5	3.5	3	0.512	1	3	3	4	Confirmed
Corporate Governance	C10	3.3	3	3	0.470	1	3	3	4	Confirmed
Market Regulations	C11	3.2	3	3	0.523	2	3	3	3.75	Confirmed
Financial Transparency	C12	3.33	3	3	0.365	1	3	3	3	Confirmed

Kendall's Coefficient: 0.886; Degree of Freedom: 11; Significance Level: 0.000

Based on the results obtained from the Delphi technique, all scores were above 3. Therefore, no component was eliminated, and all were confirmed. The Kendall statistic was also calculated as 0.886 and confirmed. Hence, Delphi results in the first round were validated. In the DEMATEL technique, experts' opinions were first collected.

Table 3

Direct-Relation Matrix Calculation

SSIM	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12
C01	0	5	5	14	14	14	16	12	16	16	12	15
C02	8	0	16	16	16	16	14	15	12	14	16	16
C03	8	6	0	16	16	16	16	16	16	16	14	16
C04	4	2	4	0	16	8	16	16	16	8	8	8
C05	4	2	4	4	0	8	16	16	16	5	8	8
C06	4	2	4	4	4	0	16	12	12	8	8	8
C07	4	2	4	3	3	0	0	12	12	8	8	8
C08	4	4	4	2	4	4	4	0	0	8	8	8
C09	4	4	4	3	3	7	8	8	0	8	8	8
C10	4	4	4	4	4	8	8	8	8	0	15	16
C11	4	4	4	4	4	8	8	8	8	8	0	16
C12	4	4	4	4	4	8	8	8	8	8	8	0

For normalization, the sum of all rows and columns of the direct-relation matrix is first calculated. The largest sum of rows and columns is denoted by k. For normalization, each element of the direct-relation matrix is divided by k.

Table 4

Direct-Relation Normalized Matrix Calculation

SSIM	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12
C01	1.000	-0.023	-0.023	-0.065	-0.065	-0.065	-0.075	-0.056	-0.075	-0.075	-0.056	-0.070
C02	-0.037	1.000	-0.075	-0.075	-0.075	-0.075	-0.065	-0.070	-0.056	-0.065	-0.075	-0.075
C03	-0.037	-0.028	1.000	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075	-0.065	-0.075
C04	-0.019	-0.009	-0.019	1.000	-0.075	-0.037	-0.075	-0.075	-0.075	-0.037	-0.037	-0.037
C05	-0.019	-0.009	-0.019	-0.019	1.000	-0.037	-0.075	-0.075	-0.075	-0.023	-0.037	-0.037
C06	-0.019	-0.009	-0.019	-0.019	-0.019	1.000	-0.075	-0.056	-0.056	-0.037	-0.037	-0.037
C07	-0.019	-0.009	-0.019	-0.014	-0.014	0.000	1.000	-0.056	-0.056	-0.037	-0.037	-0.037
C08	-0.019	-0.019	-0.019	-0.009	-0.019	-0.019	-0.019	1.000	0.000	-0.037	-0.037	-0.037
C09	-0.019	-0.019	-0.019	-0.014	-0.014	-0.033	-0.037	-0.037	1.000	-0.037	-0.037	-0.037
C10	-0.019	-0.019	-0.019	-0.019	-0.019	-0.037	-0.037	-0.037	-0.037	1.000	-0.070	-0.075
C11	-0.019	-0.019	-0.019	-0.019	-0.019	-0.037	-0.037	-0.037	-0.037	-0.037	1.000	-0.075
C12	-0.019	-0.019	-0.019	-0.019	-0.019	-0.037	-0.037	-0.037	-0.037	-0.037	-0.037	1.000

To calculate the total relation matrix, first, an identity matrix of size n×n is created. Then, this identity matrix is subtracted from the normalized matrix, and the resulting matrix is inverted. The normalized matrix is then multiplied by the inverted matrix to obtain the total relation matrix. The identity matrix is a matrix in which all elements, except for the main diagonal, are zero. The resulting matrix is the finalized total relation matrix, which can be used to calculate the causal relationship pattern.

Table 5

Total Relation Matrix (Finalized)

	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12
C01	0.021	0.039194	0.044609	0.087135	0.092902	0.097954	0.121744	0.105861	0.119912	0.112378	0.098733	0.116996
C02	0.0616	0.019821	0.097561	0.103205	0.110075	0.115437	0.12361	0.129576	0.112235	0.112612	0.124848	0.131566
C03	0.0598	0.045779	0.024638	0.099498	0.106169	0.111589	0.128341	0.130115	0.125886	0.117818	0.113071	0.127716
C04	0.0339	0.021645	0.034255	0.017198	0.09255	0.061208	0.107883	0.110195	0.106543	0.066421	0.069041	0.072595
C05	0.0318	0.020141	0.032053	0.033254	0.017686	0.057256	0.101401	0.103581	0.100148	0.049579	0.064216	0.067471

C06	0.0306	0.019236	0.030886	0.032265	0.034804	0.019484	0.098696	0.083138	0.080434	0.060569	0.062292	0.065502
C07	0.0282	0.017717	0.028449	0.025453	0.027556	0.017613	0.021355	0.076425	0.07394	0.055851	0.05738	0.060336
C08	0.0267	0.025037	0.027287	0.020273	0.030746	0.03342	0.037932	0.019986	0.01941	0.052852	0.054432	0.057239
C09	0.0287	0.026581	0.029282	0.026557	0.028576	0.049308	0.059855	0.060742	0.022675	0.056799	0.058435	0.061448
C10	0.0311	0.028701	0.031762	0.033593	0.036051	0.058174	0.06545	0.066344	0.064127	0.025516	0.093786	0.102492
C11	0.0302	0.027823	0.030791	0.032566	0.034949	0.056396	0.063449	0.064316	0.062167	0.05967	0.025417	0.099359
C12	0.0291	0.026855	0.02972	0.031434	0.033734	0.054434	0.061242	0.062079	0.060004	0.057595	0.059316	0.026338

To determine the network relation map (NRM), a threshold value must be calculated. Using this method, minor relationships can be disregarded, and only significant relationships are mapped. Only the relationships with values in matrix T greater than the threshold will be displayed in the NRM. To compute the threshold value, the mean of the values in matrix T is calculated. The threshold intensity was calculated as 0.123. Once the threshold was determined, all values in matrix T smaller than the threshold were set to zero, meaning that causal relationship was not considered.

Table 6

Significant Relationship Matrix of Study Variables

	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12
C01	X	X	X	0.087135	0.092902	0.097954	0.121744	0.105861	0.119912	0.112378	0.098733	0.116996
C02	0.0616	X	0.097561	0.103205	0.110075	0.115437	0.12361	0.129576	0.112235	0.112612	0.124848	0.131566
C03	X	X	X	0.099498	0.106169	0.111589	0.128341	0.130115	0.125886	0.117818	0.113071	0.127716
C04	X	X	X	X	0.09255	0.061208	0.107883	0.110195	0.106543	0.066421	0.069041	0.072595
C05	X	X	X	X	X	X	0.101401	0.103581	0.100148	X	0.064216	0.067471
C06	X	X	X	X	X	X	0.098696	0.083138	0.080434	X	0.062292	0.065502
C07	X	X	X	X	X	X	X	0.076425	0.07394	X	X	X
C08	X	X	X	X	X	X	X	X	X	X	X	X
C09	X	X	X	X	X	X	X	0.060742	X	X	X	0.061448
C10	X	X	X	X	X	X	0.06545	0.066344	0.064127	X	0.093786	0.102492
C11	X	X	X	X	X	X	0.063449	0.064316	0.062167	X	X	0.099359
C12	X	X	X	X	X	X	0.061242	0.062079	X	X	X	X

According to the relationship pattern, the sets of influencing and influenced factors can be determined.

Table 7

Defuzzified Total Relation Matrix (Finalized)

	C	R	C+R	C-R
C01	0.413	1.058	1.471	0.646
C02	0.319	1.242	1.561	0.924
C03	0.441	1.190	1.632	0.749
C04	0.542	0.793	1.336	0.251
C05	0.298	0.679	0.977	0.380
C06	0.646	0.618	1.264	-0.028
C07	0.991	0.490	1.481	-0.501
C08	1.012	0.405	1.418	-0.607
C09	0.947	0.509	1.456	-0.439
C10	0.828	0.637	1.465	-0.191
C11	0.881	0.587	1.468	-0.294
C12	0.989	0.532	1.521	-0.457

The sum of each row (*C*) indicates the degree of influence of that factor on other factors of the system. It is evident that land use has the highest influence on other elements of the system. The sum of each column (*R*) for each factor indicates the degree of influence that factor receives from other system elements. The horizontal vector (*C*+*R*) shows the total degree of influence and interdependence of the factor in the system. The vertical vector (*C*-*R*) indicates the power of influence of each factor. In general, if *C*-*R* is positive, the variable is considered a causal factor, and if negative, it is considered an effect factor.

The first step in Interpretive Structural Modeling (ISM) is to calculate the internal relationships of the indicators. To reflect the internal relationships among the indicators, the opinions of experts are utilized. The matrix obtained in this step shows which variable influences which other variables and which variables it is influenced by. Conventionally, to identify the pattern of relationships among the elements, symbols such as those in Table 8 are used.

Table 8

States and Symbols Used to Express the Relationships of Identified Indicators

Symbol	Meaning
V	Variable *i* influences *j*
A	Variable *j* influences *i*
X	Bidirectional relationship
O	No relationship

The Structural Self-Interaction Matrix (SSIM) is formed from the dimensions and indicators of the study and by comparing them using the four conceptual relationship states. The obtained information is summarized based on the ISM method, and the final SSIM is established. According to the symbols in Table 8, the SSIM is presented in Table 9.

Table 9

Structural Self-Interaction Matrix (SSIM)

SSIM	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12
C01		A	A	V	V	V	V	V	V	V	V	V
C02			X	V	V	V	V	V	V	V	V	V
C03				V	V	V	V	V	V	V	V	V
C04					X	A	V	V	V	A	A	A
C05						A	V	V	V	A	A	A
C06							V	V	V	A	A	A
C07								V	X	A	A	A
C08									A	A	A	A
C09										A	A	A
C10											X	X
C11												X
C12												

The matrix obtained is then converted into a binary adjacency matrix of zeros and ones. In this matrix, the diagonal elements are set equal to one. Therefore, the adjacency matrix for ISM is presented in Table 10.

Table 10

Adjacency Matrix of Identified Indicators

SSIM	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12
C01		0	0	1	1	1	1	1	1	1	1	1
C02	1		1	1	1	1	1	1	1	1	1	1
C03	1	1		1	1	1	1	1	1	1	1	1
C04	0	0	0		1	0	1	1	1	0	0	0
C05	0	0	0	1		0	1	1	1	0	0	0
C06	0	0	0	1	1		1	1	1	0	0	0

C07	0	0	0	0	0	0		1	1	0	0	0
C08	0	0	0	0	0	0	0		0	0	0	0
C09	0	0	0	0	0	0	1	1		0	0	0
C10	0	0	0	1	1	1	1	1	1		1	1
C11	0	0	0	1	1	1	1	1	1	1		1
C12	0	0	0	1	1	1	1	1	1	1	1	

The method of obtaining the reachability matrix is based on Euler's theory, in which the adjacency matrix is added to the identity matrix.

Table 11

Final Reachability Matrix of Identified Indicators

.	1 : C	2 : C	3 : C	4 : C	5 : C	6 : C	7 : C	8 : C	9 : C	10 :	11 :	12 :
1 : C1	1	0	2	21	21	11	35	43	35	8	8	8
2 : C2	2	1	2	27	27	15	43	52	43	11	11	11
3 : C3	2	2	1	27	27	15	43	52	43	11	11	11
4 : C4	0	0	0	0	1	0	3	5	3	0	0	0
5 : C5	0	0	0	1	0	0	3	5	3	0	0	0
6 : C6	0	0	0	1	1	0	5	8	5	0	0	0
7 : C7	0	0	0	0	0	0	0	1	1	0	0	0
8 : C8	0	0	0	0	0	0	0	0	0	0	0	0
9 : C9	0	0	0	0	0	0	1	1	0	0	0	0
10 : C10	0	0	0	10	10	4	20	26	20	2	3	3
11 : C11	0	0	0	10	10	4	20	26	20	3	2	3
12 : C12	0	0	0	10	10	4	20	26	20	3	3	2

To determine the relationships and leveling of the criteria, the output set and the input set for each criterion must be extracted from the adjacency matrix.

- **Reachability Set (row elements, output or influencers):** The variables that can be reached through the given variable.
- **Antecedent Set (column elements, input or influenced):** The variables through which the given variable can be reached.

The output set includes the criterion itself and the criteria it influences. The input set includes the criterion itself and the criteria that influence it. Then, the bidirectional relationship sets of the criteria are identified.

Table 12

Input and Output Sets (Influence Relationships) for Each Variable

Variable	Input: Influencing	Output: Influenced	Intersection	Level
C01	C1–C2–C3	C1–C4–C5–C6–C7–C8–C9–C10–C11–C12	C1	6
C02	C2–C3	C1–C2–C3–C4–C5–C6–C7–C8–C9–C10–C11–C12	C2–C3	7
C03	C2–C3	C1–C2–C3–C4–C5–C6–C7–C8–C9–C10–C11–C12	C2–C3	7
C04	C1–C2–C3–C4–C5–C6–C10–C11–C12–C13	C4–C5–C7–C8–C9	C4–C5	3
C05	C1–C2–C3–C4–C5–C6–C10–C11–C12–C13	C4–C5–C7–C8–C9	C4–C5	3
C06	C1–C2–C3–C6–C10–C11–C12–C13	C4–C5–C6–C7–C8–C9	C6	4
C07	C1–C2–C3–C4–C5–C6–C7–C9–C10–C11–C12–C13	C7–C8–C9	C7–C9	2
C08	C1–C2–C3–C4–C5–C6–C7–C8–C9–C10–C11–C12	C8	C8	1
C09	C1–C2–C3–C4–C5–C6–C7–C9–C10–C11–C12–C13	C7–C8–C9	C7–C9	2
C10	C1–C2–C3–C10–C11–C12–C13	C4–C5–C6–C7–C8–C9–C10–C11–C12	C10–C11–C12	5
C11	C1–C2–C3–C10–C11–C12–C13	C4–C5–C6–C7–C8–C9–C10–C11–C12	C10–C11–C12	5
C12	C1–C2–C3–C10–C11–C12–C13	C4–C5–C6–C7–C8–C9–C10–C11–C12	C10–C11–C12	5

For each variable C_i, the reachability set (output or influencing) includes the variables that can be reached through variable C_i. The antecedent set (input or influenced) includes the variables through which variable C_i can be reached. After determining the reachability and antecedent sets, their intersection is calculated. The first variable where the intersection equals the reachability set is considered the first-level variable. Thus, first-level elements have the highest level of influence in the model. After determining the level, the identified variable is removed from all sets, and the input and output sets are recalculated to determine the next-level variable.

Table 13

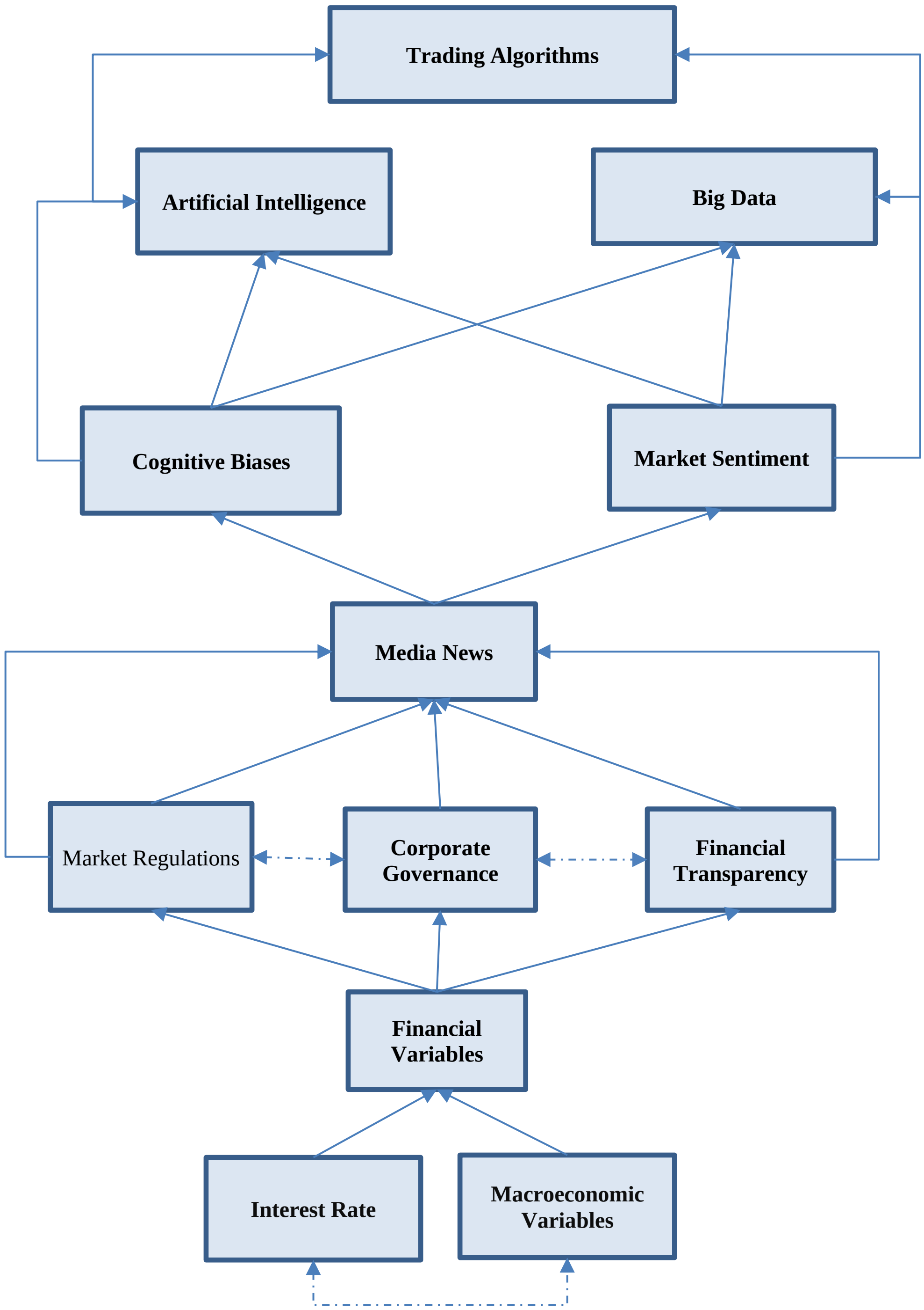
Determining the First Level in ISM Hierarchy

Row	Variables	Row Count	Column Count
1	Financial Variables	10	2
2	Macroeconomic Variables	11	1
3	Interest Rate	11	2
4	Cognitive Biases	4	8
5	Market Sentiment	4	8
6	Media News	5	6
7	Artificial Intelligence	2	10
8	Trading Algorithms	0	11
9	Big Data	2	10
10	Corporate Governance	8	5
11	Market Regulations	8	5
12	Financial Transparency	8	5
Total	73	73	

Therefore, variable C8 is identified as the first-level variable. After identifying the first-level variable(s), these are removed, and the input and output sets are recalculated without considering them. The variables whose intersections equal their input sets are then identified as second-level variables. Variables C7–C9 are second-level variables. Variables C4–C5 are third-level variables. Variables C11–C12 are fourth-level variables. The final hierarchical structure of the identified variables is illustrated in the figure. In this diagram, only the significant relationships of elements at each level with elements in the level below, as well as significant internal relationships within each row, are considered.

Figure 1

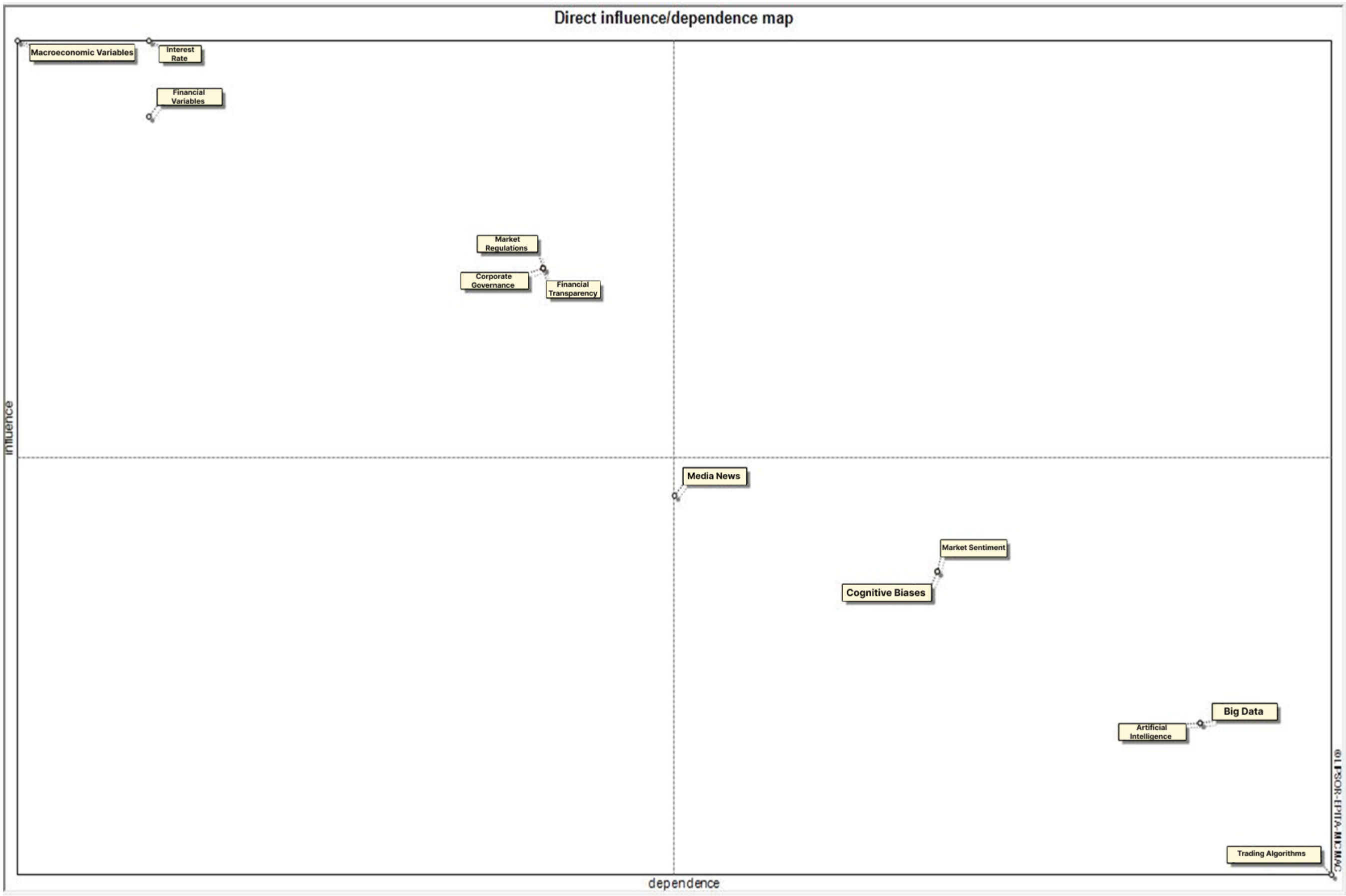
Stock Return Prediction Model Using Novel Composite Variables in the Tehran Stock Exchange



In the ISM model, the interrelationships and influences among the criteria, as well as the connections across different levels, are effectively demonstrated, which helps managers gain a better understanding of the decision-making environment. To determine the key criteria, the influence–dependency power of the criteria is calculated from the final reachability matrix. The influence–dependency diagram for the studied variables is shown in Figure 2.

Figure 2

Influence Power and Dependency Degree Diagram (MICMAC Output)



Based on the influence and dependency of the variables, a coordinate system can be defined and divided into four equal quadrants. In this study, one group of variables falls into the driving (independent) quadrant, meaning they have high driving power but low dependency. Another group consists of dependent variables, which are generally the outcomes of processes such as product development and have limited ability to drive other variables.

In this analysis, variables are classified into four groups: autonomous, dependent, linkage, and independent.

- **Autonomous:** Autonomous variables have low dependency and low driving power. These criteria are generally disconnected from the system because they have weak linkages. Changes in these variables do not lead to major system changes.
- **Dependent:** Dependent variables have strong dependency but weak driving power. They are highly influenced by the system and have little impact on it. Variables C8, C7, and C9 are dependent.
- **Independent:** Independent variables have low dependency but high driving power, meaning they exert strong influence while being weakly influenced by others. Based on the influence–dependency diagram, variables C1, C2, C3, C10, C11, and C12 fall in the independent quadrant.
- **Linkage:** Linkage variables have both high influence and high dependency. Their impact and susceptibility are both strong, so even small changes in these variables can cause significant system-wide shifts. Variables C4 and C5 are linkage variables.

4. Discussion and Conclusion

The findings of this study, which integrated DEMATEL and Interpretive Structural Modeling (ISM) with novel composite variables, reveal that stock return prediction in the Tehran Stock Exchange can be significantly enhanced when multiple domains—financial, macroeconomic, behavioral, technological, and institutional—are combined into a multi-layered model. The structural analysis identified trading algorithms (C8) as the first-level drivers, with artificial intelligence (C7) and big data (C9) emerging at the second level, cognitive biases (C4) and market sentiment (C5) occupying the third level, and institutional factors such as market regulations (C11) and financial transparency (C12) at the fourth level. This hierarchical arrangement indicates that technological enablers and digital infrastructures have become the most immediate determinants of return predictability, while behavioral and regulatory factors serve as downstream stabilizers or amplifiers.

These results are consistent with the growing evidence that predictive signals are not uniform but conditioned by regime, data frequency, and investor environment. For instance, earlier work emphasized the instability of return predictors under varying macroeconomic cycles, showing that valuation-based indicators only hold during particular economic conditions (Anderson et al., 2025; Vatsa et al., 2024). The present study adds to this body by showing that in emerging markets such as Iran, where liquidity is episodic and global shocks transmit strongly, technology-driven variables assume primacy in driving return behavior. This finding parallels international results that algorithmic trading and AI-based analytics significantly enhance market efficiency but also alter volatility clustering and short-term predictability (Akyildirim et al., 2022; Wu et al., 2020).

Moreover, the confirmation of behavioral factors such as investor sentiment and cognitive biases in the third level of the hierarchy underscores the role of non-fundamental drivers. Studies on sentiment-based volatility forecasting have already documented that investor mood and textual signals from media can provide leading information about return dynamics (Chen et al., 2022; Sakariyahu et al., 2024; Zhang et al., 2021). Our model reinforces these findings by empirically embedding sentiment alongside structural and technological variables, showing that it occupies a mediating position—translating upstream shocks into downstream pricing effects. This placement resonates with reviews of sentiment and attention cycles as "chasing noise" phenomena that nonetheless carry predictive content, particularly when integrated with machine learning pipelines (de Sousa-Gabriel et al., 2024; Sonkavde et al., 2023).

The role of macroeconomic variables and interest rates, which appeared as broader contextual drivers rather than immediate predictors, aligns with the literature on cyclical predictability. Global analyses emphasize that stock markets follow business cycle dynamics, with macro signals shaping long-term return components rather than short-term fluctuations (Kazak et al., 2024; Vatsa et al., 2024). Similarly, Iranian studies confirm that macro shocks condition volatility and liquidity in the TSE, but that their predictive power strengthens only when combined with micro and behavioral indicators (Moradi et al., 2022; Nasiri et al., 2023; Rostami et al., 2023). Our DEMATEL results echo this hierarchy, assigning macroeconomic variables to upstream roles but identifying technology and sentiment as more proximate forces.

The results also validate the inclusion of uncertainty and policy-related indices. Financial uncertainty measures, such as policy uncertainty and implied volatility, have been shown to exert significant influence on return predictability in global contexts (Huang & Luk, 2020; Liang et al., 2020; Liu et al., 2021). Our model demonstrates that when uncertainty proxies are integrated with AI-driven and algorithmic trading factors, they increase explanatory power, particularly in regimes characterized by external shocks such as the COVID-19 pandemic (Khan et al., 2024; Wang et al., 2020). This is in line with research on volatility forecasting during crises, where uncertainty indices outperformed standard predictors (Gong et al., 2022; Yan et al., 2022). Thus, institutionalizing uncertainty measures within predictive frameworks ensures robustness under turbulent market conditions.

Technological drivers emerge as the most critical enablers of predictive performance. The hierarchical placement of trading algorithms, AI, and big data reflects a market where digital infrastructure directly determines price formation, consistent with studies showing the superiority of deep learning and hybrid neural models in predicting short-term returns (Das et al., 2022; Samal & Dash, 2023; Shen & Shafiq, 2020). Iranian contributions reinforce this point: hybrid VMD-LSTM models, deep neural regime-switching architectures, and GARCH-MIDAS specifications have all shown enhanced accuracy in TSE return and volatility forecasting (Amini Mehr et al., 2021; Haghighi Naeini et al., 2023; Manjazeb et al., 2023; Nasiri et al., 2023). The current study synthesizes these strands by embedding such variables structurally rather than ad hoc, showing that technology is not just an estimation tool but a substantive driver of returns.

Institutional and governance-related variables, such as corporate governance, regulations, and transparency, were validated at higher levels of the model, suggesting their long-term impact on stability and efficiency. This aligns with findings that regulatory quality and governance mechanisms condition investor confidence and information efficiency, especially in emerging markets (Afshin Seyed Mohammad et al., 2025; Azevedo et al., 2023). While not as immediate as trading algorithms, these variables anchor the market structure, reducing asymmetry and facilitating the translation of signals into prices. Their structural placement as fourth-level elements implies that they operate as ultimate stabilizers, confirming earlier results that anomalies and factor effects weaken in high-governance environments (Anderson et al., 2025; Hasan & Al-Najjar, 2025).

The MICMAC analysis further demonstrated that independent variables such as financial ratios, macroeconomic aggregates, and institutional quality are strong drivers with low dependency, while behavioral variables such as sentiment and cognitive biases serve as linkage factors with high influence and high susceptibility. This partitioning mirrors international taxonomies of drivers and dependents, where financial fundamentals are stable but weakly reactive, while sentiment-driven variables exert disproportionate influence despite fragility (Metiu et al., 2023; H. Zhang et al., 2020). Dependent variables in our model—particularly trading algorithms and big data—represent process outcomes, highly sensitive to upstream shocks but also crucial in propagating them. Such differentiation highlights the value of causal structuring, which goes beyond black-box prediction to clarify the directional architecture of influence (Diebold & Shin, 2019; Samal & Dash, 2023).

Importantly, our findings contribute to the global debate on model uncertainty and regime dependence. Studies show that predictive relations fluctuate with business cycles, news shocks, and structural breaks (Kyriakou et al., 2020; Metiu et al., 2023). By structurally classifying variables through ISM, our approach helps identify which predictors are likely to be stable across regimes and which may fluctuate, providing a partial remedy to instability. This complements evidence that regularized combinations and ensemble learning improve robustness under model uncertainty (Diebold & Shin, 2019; Y. Zhang et al., 2020).

Finally, the present study underscores the relevance of tail-risk considerations. By incorporating variables such as big data and AI at structural cores, the model implicitly acknowledges the heavy-tailed and memory-dependent features of financial time series. Prior research on fractional dynamics and extreme value theory confirms that ignoring these properties leads to underestimated risk and weak forecast calibration (Melina et al., 2023; Tarasov, 2020). Our results suggest that a composite, structured approach can better accommodate these nonlinearities and improve predictive fidelity under extreme conditions.

This study is not without limitations. First, although it incorporates a wide range of novel composite variables, the operationalization of certain constructs—such as investor sentiment or transparency—relied on available proxies, which may not fully capture their latent dimensions. The reliance on expert judgment in constructing the DEMATEL and ISM matrices introduces subjectivity, which, despite mitigation through Delphi validation, may bias the identified hierarchies. Additionally, the model was calibrated exclusively on data from the Tehran Stock Exchange, limiting external validity; its generalizability to other emerging or developed markets remains untested. The study also emphasizes structural mapping over dynamic adaptation: while it identifies causal tiers, it does not account for how these tiers might shift across regimes, crises, or policy interventions. Finally, although advanced ML and deep learning models were discussed conceptually, empirical implementation was limited to the structural modeling stage rather than full-scale comparative testing of alternative predictive algorithms.

Future research should extend this framework by operationalizing richer, higher-frequency proxies for behavioral and technological variables, including social media attention, blockchain-based trading patterns, and AI adoption indices. Comparative validation across multiple markets—both emerging and advanced—would help establish external validity and refine the taxonomy of drivers and dependents. Scholars should also consider dynamic ISM-DEMATEL procedures that allow the causal hierarchy to evolve with changing macro and micro regimes. Integration with ensemble learning and Bayesian model averaging could further mitigate model uncertainty, providing adaptive weightings across predictors. Finally, future work should empirically test the downstream predictive performance of this structured composite framework against alternative ML and deep learning architectures, thereby quantifying the incremental value of structural causality in forecasting accuracy.

From a practical standpoint, market regulators and policymakers can use this model to identify leverage points for stabilizing returns, focusing on governance and regulatory transparency as structural anchors. Portfolio managers can employ the hierarchical insights to design multi-layered investment strategies that combine upstream financial and macro fundamentals with midstream behavioral signals and downstream technological execution. Financial institutions can enhance risk management by monitoring dependent variables such as algorithmic trading intensity, which are highly sensitive to upstream shocks. Finally, by embedding uncertainty indices and sentiment analytics into their decision pipelines, practitioners can improve resilience against crises and align predictive models with the nonlinear realities of modern capital markets.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

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