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Executive Party Characteristics and Financial Irregularities-Predictive Identification Based on Random Forest Algorithm

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ABSTRACT

As capital markets evolve, corporate financial misconduct garners more scrutiny. This study, using data from China's A-share companies (2006-2023), develops a model to predict financial irregularities with the random forest algorithm and SHAP value analysis. It analyzes the influence of corporate governance and executive party traits on non-compliance and their predictive roles. Findings indicate that financial characteristics and governance significantly impact predictions, while executive party traits have a lower influence. The model's AUC improves with the inclusion of executive party characteristics. SHAP analysis highlights feature importance and influence direction. The results offer practical insights for regulators, companies, and investors, aiding regulatory efficiency, governance optimization, and investment decisions, and guide strategies for market health.

KEYWORDS

Financial irregularities; Executive characteristics; Corporate governance; Random forest; SHAP value analysis

1. INTRODUCTION

Globalization and marketization increase capital market volatility and complexity, with frequent financial irregularities challenging market integrity. In 2023, Chinese regulators fined listed companies, highlighting the seriousness of misconduct. Such breaches harm market health by reducing transparency and investor confidence, and disrupting operations. Therefore, detecting and addressing financial irregularities is crucial. Researchers attribute causes to internal (organizational structure, management) and external (regulatory system) factors. Strong corporate governance, especially board composition, significantly affects compliance, with board size and independence ratios linked to non-compliance risks [1-4]. Moreover, informal social networks also significantly impact corporate non-compliance [5]. Additionally, a firm's financial traits like financing and operating efficiency, profitability, and cash flow correlate with its likelihood of non-compliance [6, 7]. In corporate leadership, the high-order ladder and stigma theories highlight that in uncertain, complex business settings, personal traits like age, gender, and education level significantly influence decision-making [10, 11], and personal experiences (e.g., life habits, academic studies, international work experience, and diverse career paths, etc.) [12, 13] Cognitive frameworks, behavioral habits, and value orientations, influenced by the stigma effect, significantly impact managerial decision-making and potentially lead to corporate non-compliance. Extensive research exists on the causes of non-compliance, providing a theoretical basis for early detection and prevention. However, it often concentrates on one aspect, either the company or its management, lacking a comprehensive view of governance and executive characteristics. There's a need for a holistic model to predict non-compliance, as most past studies focus on financial and non-financial indicators at the company level [14-16], Despite extensive research on motivations behind corporate violations, few models have integrated management factors into violation analysis. Traditional models using linear regression or binary choice have assessed individual impacts but lack predictive validation. Machine learning, with its data mining and predictive capabilities, provides new tools for corporate governance and finance, showing potential in forecasting violations [17]. This study develops a machine learning model for corporate violations, emphasizing governance and key corporate and executive traits. It evaluates their predictive power, enhancing governance and ladder theory understanding, and aids regulators and investors by improving regulatory efficiency and decision-making [18]. The paper innovates by combining echelon theory with governance to forecast financial irregularities, providing a holistic view and enriching the framework. It compares the predictive power of company and executive characteristics, focusing on their distinct contributions to model accuracy. The study analyzes machine learning outputs, highlighting differences in predictive power between corporate and executive features, and uses Random Forest and SHAP for model building and optimization, improving prediction accuracy and validity. SHAP's game theory approach offers clearer insights into feature contributions, quantifying the roles of financial, non-financial indicators, and executives for a more intuitive understanding of corporate violation patterns.

2. LITERATURE REVIEW

2.1. Executive Characteristics and Financial Irregularities

This study explores the roots of corporate non-compliance from internal and external perspectives. Externally, judicial independence and the consequences of disclosure act as regulators [19]. Securities analysts contribute significantly to monitoring listed companies, deterring fraud and violations [20]. Internally, governance structure and financial management are key. Board composition and equity structure are critical governance factors, with board size having a U-shaped relationship with fraud risk [21, 22]. Informal governance elements like CEO influence and director networks can both increase and curb non-compliance risks [23, 24]. He role of independent directors in curbing non-compliance is mixed; while they can strengthen controls, they might also raise collusion risks [25, 26]. Shareholding structure shows higher executive ownership typically reduces non-compliance risk by aligning interests [27, 28]. However, CEOs with equity incentives might manipulate financials, leading to violations [29]. Key financial factors include profitability, market value, and debt, with high leverage and low profitability correlating with increased non-compliance [30, 31]. Small firms and those in downturns or with debt distress are more prone to violations [31, 32]. Financial ratios are crucial for detecting fraud [33-35]. Executive characteristics play a key role in non-compliance. Senior echelon theory suggests that executives' traits like age, gender, and education influence decisions and outcomes [36-38]. Narcissistic CEOs may increase fraud risks [38]. Extrinsic attributes such as age and gender indicate that younger CEOs might have higher non-compliance risks due to inexperience, while women in leadership roles tend to be more cautious [39, 40]. Diverse executive experiences shape ethical standards and curb fraud [41]. Research on corporate non-compliance often singles out variables to see how they affect compliance. As stakeholders seek early warnings of non-compliance, scholars are developing preventive models to identify risky corporate behaviors [42]. Researchers, like De Oliveira, have developed a financial fraud identification model using corporate financial data and governance structure [43]. Researchers have created the C score, a financial fraud prediction tool tailored for China, to assess risks in listed companies against preset thresholds, identifying potential misconduct. This involves setting risk indicators for early warnings and comparing the C score with the Western M score model [44]. and F score model [45]. The C score model outperforms in China's market due to its broader variable selection and ability to capture non-linear relationships, unlike traditional models that are limited to linear relationships. Machine learning excels in identifying complex patterns and variable influence, offering a more accurate depiction of reality and better prediction for corporate violations [46].This has spurred researchers to innovate in applying machine learning for predicting corporate actions.

2.2. Machine Learning and Corporate Behaviour

The integration of machine learning into corporate finance and governance through interdisciplinary studies has accelerated financial research and improved policy evaluation accuracy [47]. Machine learning, following logical positivism, adopts a data-driven approach with supervised, unsupervised, and semi-supervised learning. Supervised learning, using labelled data, includes interpretable models like Decision Trees, effective in predicting corporate behavior [48] Other research uses decision trees for financial fraud prediction [49]. Ensemble learning, especially AdaBoost, has been shown to outperform logistic regression in predictive performance through comparative experiments, expanding the application of decision trees in corporate behavior prediction [50]. While Ada Boost is promising for complex violation models, its governance research application is limited, and there's room for improvement in interpreting feature importance in machine learning models.Machine learning predicts corporate behavior, offering insights but needing a more comprehensive and diverse modeling approach. It also struggles with variable diversity and interpretability. This study employs Random Forest and SHAP to predict financial irregularities using executives' party membership, aiming to boost prediction efficiency and accuracy by analyzing its impact and comparing model performances.

3. RESEARCH DESIGN

3.1. Variable Selection and Description

Literature links corporate governance, financial health, and executive traits to non-compliance. Using principal-agent theory, this study explores how board attributes, equity, and monitoring relate to non-compliance, analyzing 10 governance and 16 financial variables. It also considers how executive characteristics like age and gender, informed by senior ladder and stigma theories, can boost model accuracy in forecasting non-compliance, as per Bao Yang et al. [48] The study examines A-share firms (2006-2023) using CSMAR data, focusing on CEO and Chairman traits and identifying violations from CSRC notices, with a model comprising 1 target and 32 independent variables. Details are in Table 1.

Table 1. Selection and description of variables

Var Name	Def & Proc
Plan A: Corporate Violations	
Fraud	Dummy variable: 1 for actual corporate violation, 0 for none.
plan B: Financial Traits of Firms	
ROA	Net profit divided by total assets.
ROTA	Total profit over total assets.
GROSPRO	Company's total profit post-tax.
NETPRO	Profit after deducting income tax.
Asset	Sum of all assets in USD million.
ROE	Net profit to shareholders' equity ratio.
Debt	Total liabilities per item in USD million.
Size	Logarithm of year-start total assets.
Leverage	Total liabilities to total assets.
GROSS	Revenue from main business activities.
Growth	(Current year - Previous year) / Previous year's income.
TNstr	Total shares issued and circulating.
StdROE	Std. dev. of ROE over three years.
TobinQ	Market value to total assets.
Return1	Annualized returns without dividend reinvestment.
Return2	Annualized returns with dividend reinvestment.
plan C: Governance Traits	
Analyst	Number of analyst teams following the company.
Bdnum	Total directors, including the chairman.
Indep	Sole directors to board size.
NOsenior	Directors, supervisors, and senior managers total.
NOsta	Number of shares owned by state entities.
Nshrstt	State-owned shares to total share capital.
NOindep	Number independent of management and major shareholders.
Nshrsms	Shares held by insiders to total capital.
Opacity	SSE's A-D scale for corporate disclosure, with -1 for null.
sharehold	Total directors, chairman included.
plan D: Executive Party Characteristics	
EP_Execu_ratio	Ratio of party member senior executives to total.
EP_Execu	Count of party members among directors and executives.
EP_BOD_ratio	Number of party members on the board.
EP_BOD	Sum of party members on the company's board.
EP_Indep	Party members among independent directors.
EP_CEO	Binary indicator for CEO's party membership.

3.2. Descriptive Statistics

This study defines corporate violations as encompassing illegal or improper actions across financial reporting, asset management, disclosure accuracy, listing compliance, capital contribution legality, fund usage compliance, asset misappropriation, insider trading, stock trading norms, price manipulation, external guarantee compliance, and accounting practices. From 2006 to 2022, about 5% of listed companies were non-compliant, peaking near 6% in 2012. To address missing values, firm-level data used average firm values, and executive party characteristics filled gaps with averages from similar executives, prioritizing age and tenure. The financial industry was excluded. After preprocessing, the study compiled a dataset with 48,883 CEO records, ensuring no duplicate violation entries for data integrity. Table 2 outlines firm and executive characteristics.

Table 2. Decriptive Statistics

VarName	Obs	mean	sd	min	median	max
Fraud	48,883	0.0484	0.215	0	0	1
Return1	45,062	0.195	0.757	-0.924	-0.924	21.53
Return2	45,062	0.195	0.761	-0.924	-0.924	21.53
GROSS	48,878	1.094e+10	7.337e+10	-1.149e+08	-1.149e+08	3.318e+12
GROSPRO	48,883	1.197e+09	1.111e+10	-7.130e+10	-7.130e+10	4.249e+11
NETPRO	48,883	9.491e+08	8.888e+09	-6.874e+10	-6.874e+10	3.610e+11
asset	48,883	59,882	811,276	0.223	0.223	3.961e+07
debt	48,883	5.033e+10	7.449e+11	-2.033e+06	-2.033e+06	3.610e+13
TobinQ	48,883	-0.0157	9.726	-2,146	-2,146	108.4
Growth	48,396	0.0177	3.903	-207.4	-207.4	713.2
Leverage	48,883	2.153	8.621	0.609	0.609	1,739
Size	43,657	6.143	731.7	-11.33	-11.33	134,607
ROTA	48,883	0.487	4.132	-0.195	-0.195	877.3
Analyst	43,668	8.275	1.507	-1.501	-1.501	17.38
Opacity	48,883	-15,741	9.726e+06	-2.146e+09	-2.146e+09	1.084e+08
Bdnum	48,883	6.526	9.520	0	0	80
NOsenior	48,883	1.155	1.475	-1	-1	4
TNstr	48,883	16.42	3.960	2	2	54
NOsta	48,883	3.194	0.650	0	0	9
sharehold	48,883	6.331	2.451	1	1	43
Nshrsms	48,883	1.669e+09	1.202e+10	3.358e+07	3.358e+07	3.564e+11
Nshrstt	48,883	1.873e+08	3.731e+09	0	0	2.685e+11
Indep	47,166	5.248e+07	1.310e+08	0	0	4.034e+09
StdROE	48,883	0.120	0.192	0	0	0.900
EP_Execu	48,883	0.0674	0.163	0	0	0.971
EP_BOD	48,883	0.200	0.0382	0	0	0.533
EP_CEO	48,045	0.108	1.169	6.91e-05	6.91e-05	97.73
EP_Indep	48,883	1.769	2.303	0	0	22
EP_Execu_ratio	48,883	2.970	2.618	0	0	17
EP_BOD_ratio	48,883	0.431	0.495	0	0	1
Return1	48,883	0.359	0.480	0	0	1
NOindep	48,883	1.027	0.978	0	0	6
ROE	48,883	0.267	0.316	0	0	1
Return2	48,883	0.329	0.267	0	0	1

Listed companies exhibit a mean ROE of 3% and a median of 4%, with a gearing ratio averaging 41% and a median of 39%, reflecting moderate debt. Market performance is robust, as shown by a mean Tobin's Q of 2.24 and a median above 1.7. The operating revenue growth rate is 25% on average. Governance features show an average executive shareholding of 15% and state-owned shareholding of 5%, with boards averaging 8-9 members, including 20% independent directors. The transparency score averages 1.3, with 47% of firms rated good. Executive party members' distribution is diverse, with an average of 1.769 party member executives and 2.970 on boards, both showing a median of 0. The average proportion of party executives and board members is 0.267 and 0.329, respectively, with chairpersons and CEOs having higher concentrations at 0.431 and 0.359. The mean number of party member independent directors is 1.027, typically low.

3.3. Model Construction

Studies have shown financial and non-financial indicators' value in prediction models. Drawing on financial fraud models and research like Lu Yao's, this study develops two models: one based on company characteristics and another that also includes CEO party members' traits. The goal is to evaluate the significance of executive party members' characteristics in predicting corporate violations by comparing model performance with and without these traits.

Table 3. Model building

Modelling	Features	Tags
Firm Char. Model	ROA, ROTA, GROSPRO, Nshrsms, Opacity, NETPRO, asset, sharehold, ROE, debt, Size, Leverage, GROSS, Growth, TNstr, StdROE, TobinQ, Return1, Analyst, Return2, Bdnum, Indep, NOsenior, NOsta, Nshrstt, NOindep	Fraud
CEO Char. Model	TROA, ROTA, GROSPRO, Nshrsms, Opacity, NETPRO, asset, sharehold, ROE, debt, Size, Leverage, GROSS, Growth, TNstr, StdROE, TobinQ, Return1, Analyst, Return2, Bdnum, Indep, NOsenior, NOsta, Nshrstt, NOindep, EP_Execu_ratio, EP_Execu, EP_BOD_ratio, EP_BOD, EP_Indep, EP_CEO	

The study's empirical analysis is divided into three parts. First, it creates a predictive model with the Random Forest algorithm. To handle the data imbalance, where non-violating companies outnumber violators by 5-6 times, the study modifies the sample data following Bertomeu et al.'s approach, avoiding a standard yearly window method [50].

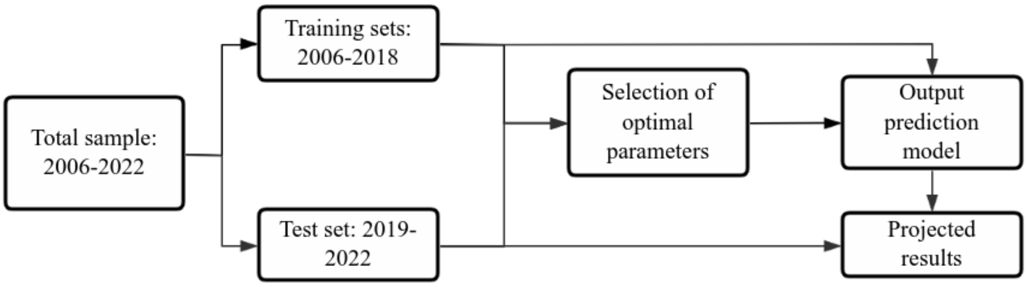

Figure 1. Experimental Procedure

The study develops a predictive model on the training set, with the validation set monitoring progress and tuning hyper-parameters. The test set (2019-2022) assesses real-world performance. Undersampling balances the ratio due to fewer offending firms, refining model training [50]. Model efficacy is measured by AUC across two datasets, indicating the ability to distinguish between classes. A threshold

Table 4. Confusion mMtrix

true class	hypothesized class	
	0	1
0	True Negatives	False Positives
1	False Negatives	True Positives

Accuracy reflects the model's correct predictions out of the total sample

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

Precision is the ratio of true positives in the predicted positives, and Recall is the ratio of true positives to actual positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

PE is the precision at a given recall level, and Kappa measures classifier performance, accounting for random agreement probability.

$$\text{K} = \frac{p_o - p_e}{1 - p_e} \tag{4}$$

F_score balances precision and recall.

$$\text{F\_score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \tag{5}$$

He studies uses SHAP analysis to evaluate feature importance in financial irregularity prediction, then tests model robustness by replacing key features with chairman party features, adjusting parameters, and conducting additional model tests.

4. ANALYSIS OF EMPIRICAL RESULTS

4.1. Output Result

Table 5. Random Forest Output Results

Dataset	Indicators	Company (1)	CEO Party (2)	Efficiency %
Training	auc_train	0.996	0.998	0.23
Test	auc_test	0.741	0.741	-0.11
	Accuracy	0.955	0.955	0.01
	Precision	0.359	0.402	11.95
	Recall	0.037	0.056	54.38
	PE	0.953	0.951	-0.15
	K	0.059	0.089	51.78
	F_score	0.066	0.099	49.15

The study uses Random Forest to construct models based on company and CEO party member characteristics, evaluating them on a sample dataset. Both models show high performance in predicting corporate violations, with AUC values above 90% on the validation set and nearly 80% on the test set, indicating strong classification capabilities. Figure 2 presents the ROC curves, plotting FPR against TPR, with AUCmeasures the predictive power of the model, independent of a specific threshold. This metric is vital for assessing the model's predictive effectiveness.

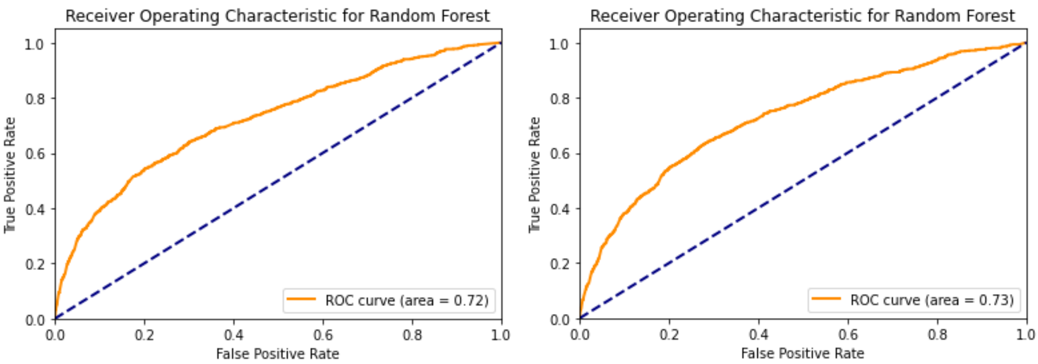

Figure 2. ROC plot of company characteristics (left), ROC plot of CEO party characteristics (right)

Comparing the two models' AUC values, adding party member characteristics slightly improves predictive ability but not significantly in forecasting violations, with both showing an AUC of 0.741 on the test set. The CEO party feature model (model 2) has higher test set accuracy (0.95), Precision (0.40), and Recall (0.056) than the company profile model (Precision 0.36, Recall 0.036) in identifying violators. However, due to the low proportion of actual violators (15%), precision and recall remain low, necessitating threshold adjustments to balance them for regulatory purposes. The low Kappa coefficients for both models indicate room for improvement through additional features or algorithm optimization.

4.2. Characteristic Importance Analysis

This study builds a CEO party member characteristic prediction model using Random Forest and analyzes feature contributions with SHAP. Fig. 3 ranks feature by their mean absolute SHAP values, identifying key non-compliance predictors. The plot visualizes each feature's impact on predictions, with points showing sample influence and colors indicating feature value magnitude.

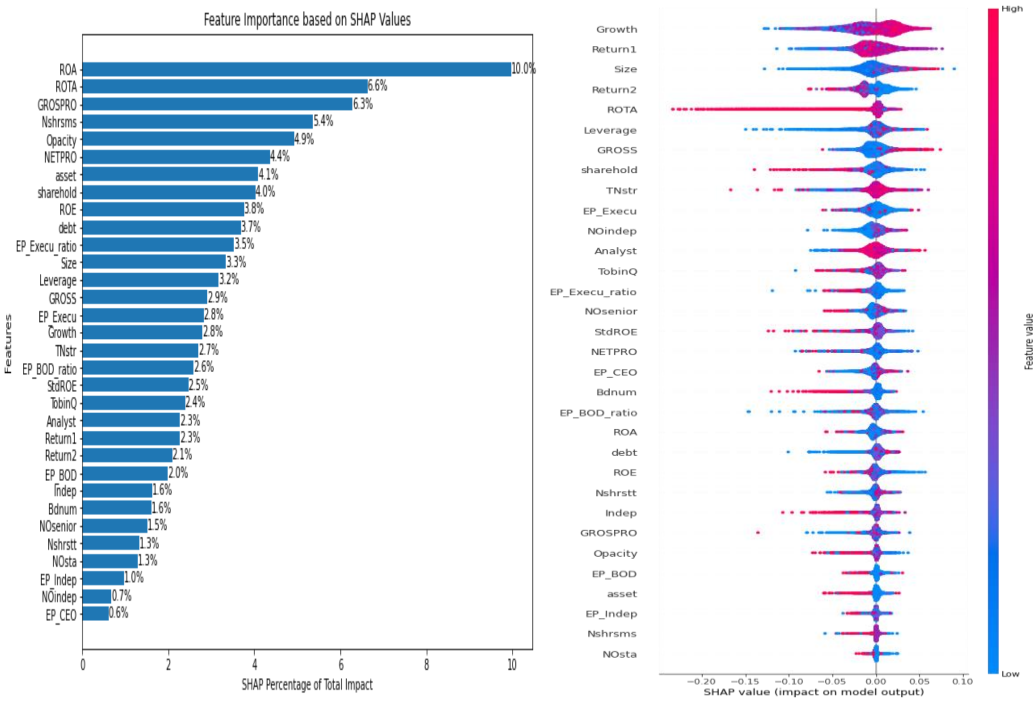

Figure 3. Importance Ranking Chart (left) and Summary Chart (right)

Financial and governance factors dominate, explaining 57.78% and 29.74% of the model's weight, respectively. ROA and ROTA are major predictors at 10% and 6.6%, and executive share ownership significantly affects compliance. CEO party membership impacts the model at 12.48%, and the proportion of party executives at 3.5%. Other indicators are categorized by importance, showing their relative influence on compliance prediction. This analysis highlights the importance of financial health and governance structure in detecting corporate irregularities.

4.3. Characteristic Importance Analysis

SHAP dependency graph for the importance of CEO party characteristics with contribution and trend analysis.

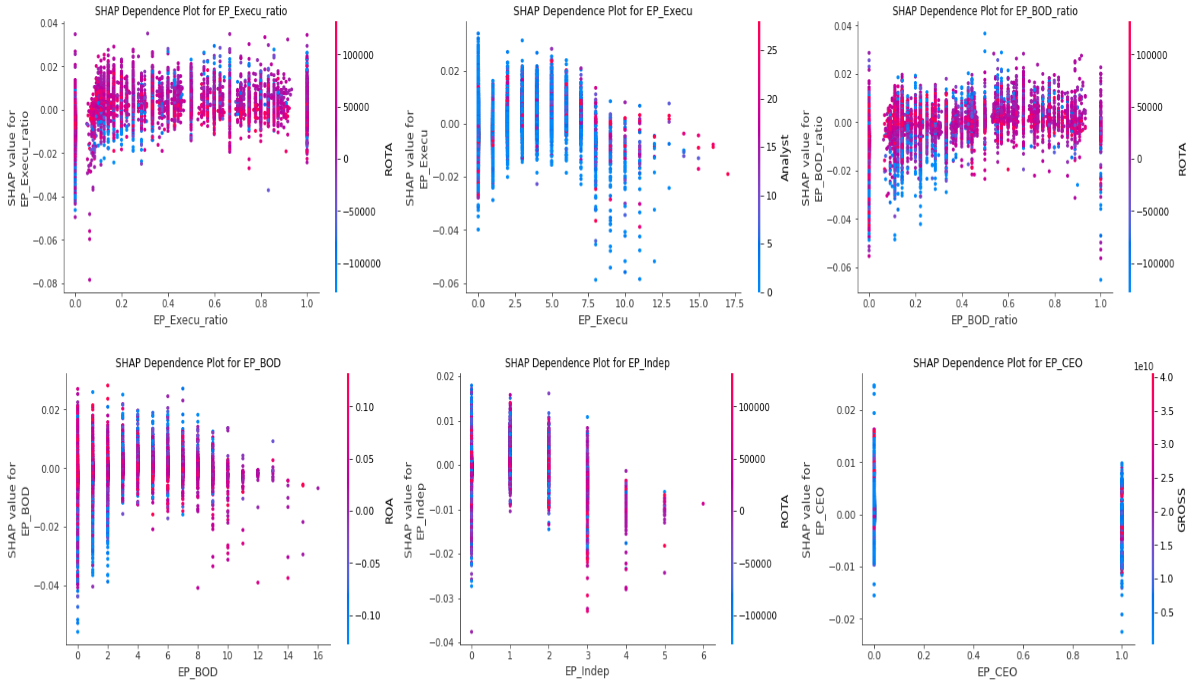

Figure 4. CEO Party SHAP Dependency Chart

The SHAP dependence plot for party member executives (EP_Execu), board members (EP_BOD), independent directors (EP_Indep), and CEO party membership (EP_CEO) shows a negative correlation, indicating higher values of these characteristics decrease the model's prediction of financial violations, suggesting an effective supervisory role in governance. The SHAP values for the proportions of these groups (EP_Execu_ratio, EP_BOD_ratio) do not clearly indicate a relationship, as their impact depends on the total numbers (EP_Execu, EP_BOD), making the trend less apparent.

5. ROBUSTNESS CHECK

5.1. Replacement of Key Variables

In order to ensure the robustness of the research conclusions, this paper replaces the core variable whether the CEO is a member of the party (EP_CEO) with whether the chairman is a member of the party (EP_Chair), the CEO pays more attention to the company's short-term operation and goal achievement, while the chairman tends to focus on the company's governance and long-term strategy, and the characteristics of the party members of the executives will have a positive effect on the executives' own professional behaviours, and the chairman is predicted by the Random Forest model. party characteristics model is predicted, and the prediction results are shown in Table 6.

Table 6. ResultsReplacement of variable output results

Dataset	Indicators	Company (1)	Chairman's Party (3)	Efficiency %
Training	auc_train	0.996	0.999	0.30
Test	auc_test	0.741	0.727	-1.89
	Accuracy	0.955	0.955	0.00
	Precision	0.359	0.355	-1.11
	Recall	0.037	0.042	13.51
	PE	0.953	0.952	-0.10
	K	0.059	0.067	13.56
	F_score	0.066	0.075	13.64

The results remain robust after core variable substitution. In particular, the AUC values for both models are close to 99% for the training set and close to 73% for the test set, indicating that the models have a more significant classification ability. Precision and Recall both remain within a relatively close range of values. The chairman of the party feature model is better than the company feature model in both the check all rate (K) and the check accuracy rate (F_score), and has better generalisation ability.

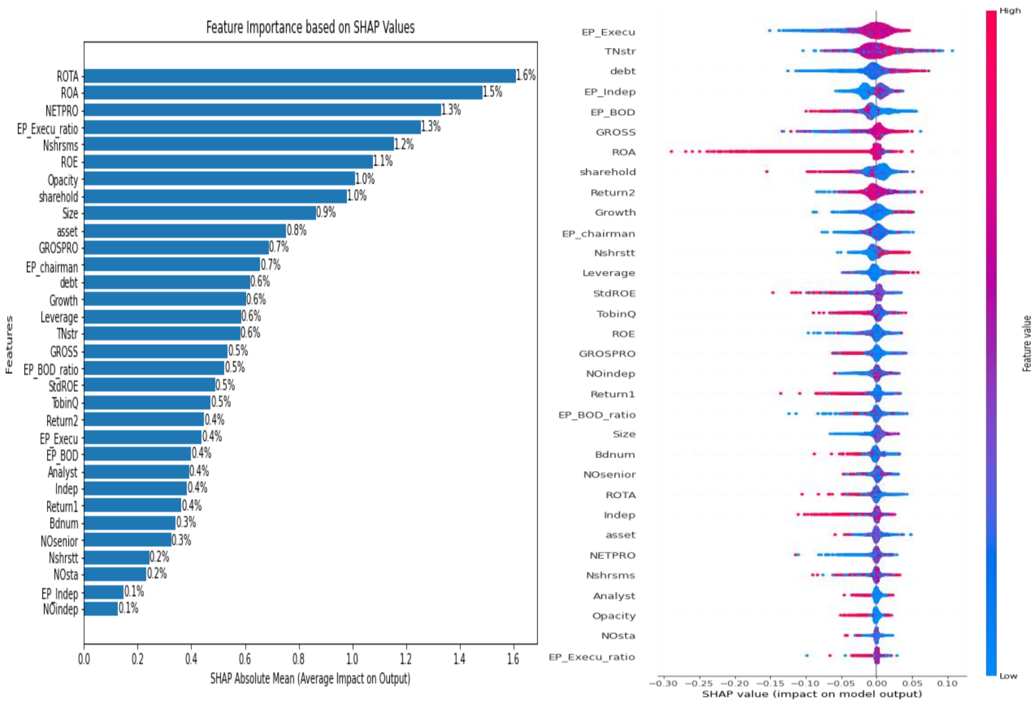

Figure 5. Chairman's model importance ranking chart (left) and summary chart (right)

Fig. 5 indicates that the model's feature importance order remains largely unchanged, with financial metrics like ROTA and ROA leading in influence on prediction outcomes. Despite altering party characteristic variables, model stability is maintained, showing significant classification capabilities with AUC values around 99% for training and approximately 73% for testing. Precision and Recall are consistently close, and the party chairman feature model outperforms the company feature model in both Kappa (K) and F-score, demonstrating superior generalization.

5.2. Changing the Adjustment Parameters

The study identifies key parameters like n_estimators and max_depth for both company and CEO party member models, recognizing their impact on model outcomes and robustness. Optimal parameters are determined by varying these and comparing results, as presented in Table 9. The best model configuration, with n_estimators set to 15 and max_depth to 20, yields an AUC of 74%, outperforming other combinations in terms of accuracy, precision, and recall, thus validating the model's robustness.

Table 7. Tuning Output Results

n_estimators	max_depth	Indicators	Company (1)	CEO Party (2)	Efficiency %
Plan A: Outputs of this study					
15	20	auc_test	0.741	0.741	-0.11
		Precision	0.359	0.402	11.95
		Recall	0.037	0.056	54.38
Plan B: Tuning Output Results					
15	25	auc_test	0.721	0.726	0.69
		Precision	0.275	0.347	26.18
		Recall	0.025	0.047	88.00
10	20	auc_test	0.687	0.701	2.04
		Precision	0.222	0.306	37.84
		Recall	0.031	0.043	38.71
10	25	auc_test	0.696	0.699	0.43
		Precision	0.257	0.356	38.52
		Recall	0.034	0.042	23.53
20	20	auc_test	0.740	0.753	1.76
		Precision	0.311	0.254	-18.33
		Recall	0.025	0.034	36.00
20	25	auc_test	0.749	0.744	-0.67
		Precision	0.357	0.400	12.04
		Recall	0.033	0.210	-36.36

6. SUMMARY

This study, grounded in high-order ladder and corporate governance theories, examines corporate financial, governance, and executive party member characteristics as core variables. It utilizes a random forest algorithm to construct a financial violation prediction model for listed companies from 2006 to 2022, enhanced by SHAP analysis. The model predicts financial irregularities with improved accuracy; the CEO's party membership model outperforms others, enhancing the AUC by 23% and precision/recall rates. Despite this, executive party traits' contribution to prediction is limited. However, a higher number of party member executives correlates with reduced financial violations, indicating their role in constraining and supervising financial practices. The model provides insights into the impact of various characteristics on financial violations, aiding in corporate governance understanding and improvement.

This study offers practical insights for regulators, companies, and investors. Regulators should establish clear guidelines for disclosing executive party membership to enhance market assessment accuracy, promote regular legal training for party executives, and create incentives linking governance performance to executive rewards. Companies should optimize board composition with party members for better decisions, strengthen internal controls, and disclose governance practices for transparency. Investors should consider executive party traits in risk assessment, analyze their impact on corporate governance and financial transparency, and actively engage in shareholder meetings to foster governance improvements, supporting sustainable corporate growth.

REFERENCES

[1] Zhao, J., et al., (2024). Independent directors' performance behavior and corporate violations. Finance research letters, 69: pp. 106119.

[2] Xu, J., Z. Jia and B. Liu, (2024) Can independent directors' green experience curb corporate environmental violations: Evidence from Chinese heavily polluting listed companies. Finance Research Letters, 67: ppp. 105836.

[3] Guo, p., (2022) Audit Committee Disclosure Tone and Corporate Violations in China: Textual Analysis. Mobile Information Systems, 2022.: pp. 1-11.

[4] Sun, R., et al., Machine Learning for Predicting Corporate Violations: How Do CEO Characteristics Matter? Journal of business ethics, 2024.

[5] Yuan, X., et al., ESG disclosure and corporate financial irregularities – Evidence from Chinese listed firms. Journal of cleaner production, 2022. 332: pp. 129992.

[6] Kreutzfeldt, R.W. and W.A. Wallace, Error characteristics in audit populations: their profile and relationship to environmental factors. Auditing: a journal of practice and theory, 1986. 6: pp. 20.

[7] Li, X. and Y. Li, Female independent directors and financial irregularities in chinese listed firms: From the perspective of audit committee chairpersons. Finance research letters, 2020. 32: pp. 101320.

[8] Liao, J., D. Smith and X. Liu, Female CFOs and accounting fraud: Evidence from China. Pacific-Basin finance journal, 2019. 53: pp. 449-463.

[9] Li, V., Groupthink tendencies in top management teams and financial reporting fraud. Accounting and business research, 2024. 54(3): pp. 255-277.

[10] Jebran, K., S. Chen and Y. Chen, The consequences of sibling rivalry: Board chair birth order and corporate misconduct. Asia Pacific journal of management, 2024.

[11] Van Scotter, J.R. and K. De Déa Roglio, CEO Bright and Dark Personality: Effects on Ethical Misconduct. Journal of business ethics, 2020. 164(3): pp. 451-475.

[12] Hsieh, T., et al., Educate to innovate: STEM directors and corporate innovation. Journal of business research, 2022. 138: pp. 229-238.

[13] Gen, W., et al., Corporate social responsibility and corporate financial fraud: evidence from China. JAAF (Journal of Applied Accounting and Finance), 2022. 6(1): pp. 38.

[14] Xu, Y., L. Zhang and H. Chen, Board age and corporate financial fraud: An interactionist view. Long range planning, 2018. 51(6): pp. 815-830.

[15] Xue, S., et al., How boards' factional faultlines affect corporate financial fraud. Asia Pacific journal of management, 2024. 41(1): pp. 351-376.

[16] Zhou, H., et al., Internet Financial Fraud Detection Based on a Distributed Big Data Approach With Node2vec. IEEE access, 2021. 9: pp. 43378-43386.

[17] Shou, M., X. Bao and J. Yu, An optimal weighted machine learning model for detecting financial fraud. Applied Economics Letters, 2023. 30(4): pp. 410-415.

[18] Gong, G., et al., Punishment by Securities Regulators, Corporate Social Responsibility and the Cost of Debt. Journal of business ethics, 2021. 171(2): pp. 337-356.

[19] Zuo, Y., et al., Corporate Misconduct and Analyst Forecasting Accuracy: Evidence from China. EMERGING MARKETS FINANCE AND TRADE, 2022.

[20] Avci, S.B., C.A. Schipani and H.N. Seyhun, Do Independent Directors Curb Financial Fraud? The Evidence and Proposals for Further Reform. INDIANA LAW JOURNAL, 2018. 93(53): pp. 757-805.

[21] Ma, Y., et al., Corporate governance, technological innovation, and corporate performance: Evidence from China. HELIYON, 2024. 10(e3145911).

[22] Kim, D.S. and S. Lee, Board political connections and financial fraud: The case of business groups in South Korea. ASIA PACIFIC JOURNAL OF MANAGEMENT, 2023.

[23] Chahine, S., et al., CEO Network Centrality and the Likelihood of Financial Reporting Fraud. ABACUS-A JOURNAL OF ACCOUNTING FINANCE AND BUSINESS STUDIES, 2021. 57(4): pp. 654-678.

[24] Khanna, V., E.H. Kim and Y. Lu, CEO Connectedness and Corporate Fraud. JOURNAL OF FINANCE, 2015. 70(3): pp. 1203-1252.

[25] Lyu, X.L. and X. Zhang, Corporate fraud and independent director's re-appointment: Information hypothesis or favouritism hypothesis? ACCOUNTING AND FINANCE, 2024.

[26] Armstrong, C.S., A.D. Jagolinzer and D.F. Larcker, Chief Executive Officer Equity Incentives and Accounting Irregularities. JOURNAL OF ACCOUNTING RESEARCH, 2010. 48(2): pp. 225-271.

[27] Tutino, M. and M. Merlo, Accounting fraud: A literature review. Risk Governance and Control: Financial Markets and Institutions, 2019. 9(1): pp. 8-25.

[28] Harris, J. and pp. Bromiley, Incentives to Cheat: The Influence of Executive Compensation and Firm Performance on Financial Misrepresentation. Organization science (Providence, R.I.), 2007. 18(3): pp. 350-367.

[29] Farrell, K.A., J. Yu and Y. Zhang, What are the Characteristics of Firms that Engage in Earnings Per Share Management Through Share Repurchases? Corporate governance: an international review, 2013. 21(4): pp. 334-350.

[30] Loncarski, I. and L. Vidovic, Sorting out the financials: Making economic sense out of statistical factors. FINANCE RESEARCH LETTERS, 2019. 31: pp. 110-118.

[31] Leng, F., et al., The Long-Term Performance and Failure Risk of Firms Cited in the US SEC's Accounting and Auditing Enforcement Releases. JOURNAL OF BUSINESS FINANCE & ACCOUNTING, 2011. 38(7-8): pp. 813-841.

[32] KHANNA, V., E.H. KIM and Y. LU, CEO Connectedness and Corporate Fraud. The Journal of finance (New York), 2015. 70(3): pp. 1203-1252.

[33] Kaminski, K.A., T. Sterling Wetzel and L. Guan, Can financial ratios detect fraudulent financial reporting? Managerial auditing journal, 2004. 19(1): pp. 15-28.

[34] Huang, A.H., pp. Kraft and S. Wang, The Usefulness of Credit Ratings for Accounting Fraud Prediction. ACCOUNTING REVIEW, 2023. 98(7): pp. 347-376.

[35] Chakrabarty, B., et al., Catch me if you can: In search of accuracy, scope, and ease of fraud prediction. REVIEW OF ACCOUNTING STUDIES, 2024.

[36] Nyberg, A.J., O.R. Cragun and D.J. Schepker, Chief Executive Officer Succession and Board Decision Making: Review and Suggestions for Advancing Industrial and Organizational Psychology, Human Resources Management, and Organizational Behavior Research, in Annual Review of Organizational Psychology and Organizational Behavior, F. pp. Morgeson, F. pp. Morgeson^Editors. 2021, ANNUAL REVIEWS: PALO ALTO. pp. 173-198.

[37] Rijsenbilt, A. and H. Commandeur, Narcissus Enters the Courtroom: CEO Narcissism and Fraud. JOURNAL OF BUSINESS ETHICS, 2013. 117(2): pp. 413-429.

[38] Trabert, S., Do younger CEOs really increase firm risk? Evidence from sudden CEO deaths. Journal of corporate finance (Amsterdam, Netherlands), 2023. 79: pp. 102367.

[39] Sewon, O., Z. Iqbal and H. Baek, Are Female Executives More Risk-Averse than Male Executives? Atlantic economic journal, 2006. 34(1): pp. 63-74.

[40] Xiang, R. and W. Zhu, Academic independent directors and corporate fraud: evidence from China. Asia-Pacific journal of accounting & economics, 2023. 30(2): pp. 285-303.

[41] De Oliveira, W.D.C. and D.S. Monte-Mor, The Influence of the Organizational Life Cycle on the Violation of Financial Covenants. RBGN-REVISTA BRASILEIRA DE GESTAO DE NEGOCIOS, 2022. 24(4): pp. 708-722.

[42] Price, R.A.I., N.Y. Sharp and D.A. Wood, Detecting and Predicting Accounting Irregularities: A Comparison of Commercial and Academic Risk Measures. ACCOUNTING HORIZONS, 2011. 25(4): pp. 755-780.

[43] Beneish, M.D., The Detection of Earnings Manipulation. Financial analysts journal, 1999. 55(5): pp. 24-36.

[44] DECHOW, pp.M., et al., Predicting Material Accounting Misstatements. Contemporary accounting research, 2011. 28(1): pp. 17-82.

[45] Gu, S., et al., Empirical Asset Pricing via Machine Learning. The Review of financial studies, 2020. 33(5): pp. 2223-2273.

[46] Kou, G., et al., MACHINE LEARNING METHODS FOR SYSTEMIC RISK ANALYSIS IN FINANCIAL SECTORS. TECHNOLOGICAL AND ECONOMIC DEVELOPMENT OF ECONOMY, 2019. 25(5): pp. 716-742.

[47] Al, L.Y.Z.Y., Managerial individual characteristics and corporate performance: Evidence from a machine learning approach. Journal of Management Sciences in China, 2020. 23(02): pp. 120-140.

[48] Bao, Y., et al., Detecting Accounting Fraud in Publicly Traded US Firms Using a Machine Learning Approach. JOURNAL OF ACCOUNTING RESEARCH, 2020. 58(1): pp. 199-235.

[49] Troy, C., K.G. Smith and M.A. Domino, CEO demographics and accounting fraud: Who is more likely to rationalize illegal acts? Strategic organization, 2011. 9(4): pp. 259-282.

[50] Bertomeu, J., et al., Using machine learning to detect misstatements. REVIEW OF ACCOUNTING STUDIES, 2021. 26(2): pp. 468-519.