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Financial signals and governance in fraud detection: Evidence from Indonesia's energy sector using logistic regression and random forest

Sherena Wahyutari
Universitas Muhammadiyah
INDONESIA

Triyono
Universitas Muhammadiyah
INDONESIA

Banu Witono
Universitas Muhammadiyah
INDONESIA

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Abstract

Background: Fraud in financial reporting still appears in Indonesia's energy industry, a field where complex operations often conceal early signs of misstatements. In many cases, day-to-day financial patterns reveal more dependable clues than the formal structure of corporate governance.
Aim: The study examines how governance features and financial indicators contribute to identifying possible manipulation in financial statements and evaluates the predictive strength of logistic regression compared with Random Forest.
Method: The analysis uses 171 firm-year observations from energy companies listed on the Indonesia Stock Exchange between 2022 and 2024. Potential irregularities were screened using the Beneish M-Score. Governance information covers the share of independent commissioners, CEO duality, board size, and board meeting frequency, while profitability, operating cash flow, and sales growth serve as the financial indicators. Both logistic regression and Random Forest were employed, and their performance was reviewed through accuracy, sensitivity, specificity, and AUC values.
Results: Governance variables showed no meaningful link to the likelihood of fraud. In contrast, profitability, operating cash flow, and sales growth consistently appeared as significant indicators. Logistic regression produced stronger classification results, reaching 79.4 percent accuracy with an AUC of 0.814, compared with Random Forest's 70.6 percent accuracy and 0.731 AUC.
Conclusion: Financial indicators proved more reliable than governance characteristics in signaling possible fraudulent reporting. Logistic regression also offered steadier predictive behavior than Random Forest, making it particularly useful for monitoring firms in the Indonesian energy sector.

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INTRODUCTION

Concerns over the accuracy of financial reporting in Indonesia's energy sector continue to grow, creating a sense of urgency for studies that examine the roots of these irregularities Concerns over the accuracy of financial reporting in Indonesia's energy sector continue to grow, creating a sense of urgency for studies that examine the roots of these irregularities (Sambodo et al., 2024a; Widhiyani et al., 2025). The sector plays a substantial role in national revenues, making any form of misstatement more than a company-level problem. Many firms operate with complex production chains that require long planning horizons, creating situations where performance cannot be assessed quickly. This delay often gives management considerable room to interpret financial results. When financial figures depend heavily on estimates, external reviewers struggle to determine whether deviations are the result of genuine uncertainty or intentional manipulation. Past events in the sector demonstrate that misstatements can persist for years before drawing regulatory attention (Bartov et al., 2021; L. Yang & Zhu, 2025). Such patterns weaken trust among investors who rely

*** Corresponding author:**
Sherena Wahyutari, Muhammadiyah University, INDONESIA
sherenawahyutari@gmail.com

heavily on financial statements for decision-making. This combination of strategic importance and persistent irregularities creates a strong need for studies that revisit fraud indicators in this industry.

Energy companies often rely on technical forecasts related to reserves, production volumes, and extraction costs, all of which require substantial expertise to evaluate. Because most stakeholders do not have access to detailed engineering data, financial disclosures become the primary window into firm performance. This dependence increases the vulnerability of the sector when managers choose reporting assumptions that subtly distort reality (Acuti et al., 2024; Carter, 2021). A small shift in reserve estimates, for example, can alter asset valuations in ways that are difficult to challenge. The opacity surrounding these assumptions makes it easier for misstatements to escape scrutiny. Investors, lenders, and regulators frequently lack the means to independently verify such technical inputs. These conditions illustrate why the energy sector is repeatedly mentioned in discussions of reporting irregularities (Arvidsson & Dumay, 2022; Minutti-Meza, 2021). They also underscore the need to identify indicators that remain reliable even when technical information is limited.

Several well-known Indonesian cases reveal how financial reporting can be manipulated within the sector (Prabowo, 2023; Sari et al., 2021). Reports of overstated revenue, questionable asset valuations, and concealed liabilities have surfaced at various times. These incidents typically arise during periods when companies face declining market conditions. Falling commodity prices, rising operating costs, or tightening credit environments put pressure on managers to maintain the appearance of stability. Such pressure can motivate the use of accounting choices that hide operational weaknesses (Chan & Gibbs, 2022; Mandal & S., 2023). Once misreporting becomes routine, reversing the pattern becomes increasingly difficult without attracting public attention. The delay between the start of manipulation and its eventual discovery has proved costly in several cases. Understanding how such events start and persist provides an important backdrop for examining fraud indicators more closely.

Corporate governance is expected to reduce the likelihood of fraud by ensuring that management is held accountable. However, the effectiveness of governance structures varies considerably across Indonesian energy firms (Rudenko & Tanasov, 2020; Setyowati, 2021). In several companies, board members are appointed through political or administrative channels rather than selected for industry expertise. This situation creates gaps in oversight, particularly when board members are unable to challenge complex technical assumptions. Oversight becomes even more complicated when firms operate across multiple subsidiaries or joint ventures. Decision-making structures may become fragmented, creating opportunities for misaligned incentives (Menard et al., 2021; Zhang & Sun, 2022). These realities make it difficult to assume that governance mechanisms always function as intended. As a result, relying on governance alone may leave undetected risks that require more nuanced tools.

Financial indicators offer an alternative source of insight because they are tied directly to operational activity. Profitability, cash flow, and revenue trends often reveal movements that cannot easily be hidden through accounting choices (Séverin & Veganzones, 2021; Shang & Chi, 2023). When these indicators begin to diverge from reported results, they can signal potential manipulation. Researchers have long recognized that firms experiencing declining performance face greater temptation to adjust their financial statements (S. Yang, 2022). In the energy sector, rapid shifts in market conditions can produce abrupt changes in financial patterns. These changes sometimes appear before the effects can be fully explained through narrative disclosures. Because of this, financial indicators may capture early irregularities more consistently than governance features. They represent a practical and accessible tool for stakeholders who lack technical information.

Alongside these substantive concerns, analytical methods have evolved significantly. Traditional techniques like logistic regression remain valuable because they reveal how individual indicators relate to fraud likelihood (Knuth & Ahrholdt, 2022; Mishra, 2025). Their transparency allows regulators and auditors to understand why a firm is classified as high risk. However, newer machine-learning approaches such as Random Forest offer the ability to examine broad, non-linear patterns that may escape classical methods. These models consider complex interactions without requiring strict statistical assumptions. Yet the interpretive advantages of logistic regression still make it appealing in regulatory contexts. This tension between interpretability and predictive strength highlights the need for direct comparisons (Alangari et al., 2023; Li et al., 2022). Evaluating both approaches within a single sector can clarify their respective strengths.

The structure of the Indonesian energy industry creates conditions well suited for comparing analytical models. Firms differ widely in ownership composition, operational scale, and exposure to global markets(Cuervo-Cazurra et al., 2025; Greenstone et al., 2023). These differences lead to diverse financial trajectories even within the same sector. Global price volatility often causes abrupt swings in financial performance, highlighting the need for models that can manage noisy or unstable data. Governance characteristics can also differ sharply between state-owned firms and private companies. These variations create a rich environment for testing whether traditional or machine-learning models perform better (Janiesch et al., 2021; Zhu et al., 2023). Such comparisons have practical value for auditors and regulators who require dependable tools to identify early signs of misstatement.

Given this combination of technical opacity, governance challenges, and volatile financial patterns, research on fraud detection within Indonesia's energy sector is both timely and necessary (Sambodo et al., 2024b). The stakes are high because misstatements in this industry can influence national planning, investment flows, and public confidence. A study that considers both governance and financial indicators provides a fuller understanding of where early warning signals may originate. Examining logistic regression alongside Random Forest helps determine whether classical or modern analytical strategies are more suitable for this type of data. Insights from such a comparison can guide more effective fraud detection frameworks (Nesvijevskaia et al., 2021). They may also support the refinement of monitoring practices in sectors facing similar risks. Ultimately, this research contributes to strengthening financial transparency in an industry that plays a central role in Indonesia's economic stability.

Work on fraudulent financial reporting continues to show that governance structures in emerging markets often operate more as formal requirements than effective safeguards, a point illustrated. Notes that the Beneish M-Score remains useful, yet its accuracy improves considerably when combined with financial indicators that reflect real operational pressure. The role of profitability, cash flow, and sales dynamics appears repeatedly in studies by Nguyen (2023),each showing that financial strain leaves clearer traces than board composition alone. These patterns echo long-standing ideas within the Fraud Triangle, which views pressure as a key step toward misconduct. (Liu, 2025) show how Random Forest models can identify irregular patterns that simple linear methods would miss. A similar improvement in predictive strength is reported by (Messele, 2025), who works with ensemble learning in educational data. The value of more complex structures is further demonstrated by Bangian Tabrizi et al. (2025) and Zhou (2025), both of whom use graph-based and neural architectures to map hidden relationships in dense datasets. Even so, logistic regression remains relevant when interpretability is needed, as shown convincingly in Ozen et al. (2025). Regression also forms the backbone of analytical work in McCormick et al. (2025) and Rahimi et al. (2025), who rely on its stability across biological and health-related measurements. Studies by Lin et al. (2025) and Morgan & Hu (2025) illustrate how statistical modeling can expose subtle behavioral patterns that descriptive analysis overlooks. Taken together, these findings indicate that governance variables rarely capture manipulation effectively in sectors marked by operational complexity, such as energy. A blended approach—drawing on financial indicators, logistic regression, and modern machine learning—offers a more dependable route for identifying fraud risk in this setting.

The energy sector in Indonesia operates within a landscape shaped by technical uncertainty, fluctuating revenues, and complex ownership arrangements, all of which make transparency in financial reporting difficult to maintain. In such an environment, traditional governance mechanisms often fall short because boards and oversight bodies may lack the technical capacity to challenge accounting estimates that depend heavily on managerial judgment. Although corporate governance reforms have been widely promoted, their practical influence on detecting misstatements remains limited. By contrast, financial indicators reflect operational realities more directly and often shift in response to pressures that precede fraudulent activity. At the same time, the availability of analytical tools ranging from classical statistical models to machine-learning techniques creates an opportunity to reassess the signals that truly matter in detecting financial manipulation. The rationale for this study therefore lies in the need to examine whether fraud is more accurately captured through financial indicators than governance structures and to evaluate the extent to which modern analytical approaches add value in this context.

Despite the substantial body of research on fraudulent financial statements in Indonesia, much of the existing work leans heavily on governance variables whose empirical impact has been inconsistent and often weak. These mixed results suggest that governance structures may operate more symbolically than effectively, particularly in sectors that rely on estimation-heavy accounting practices such as reserve valuation and long-term contract recognition. Prior studies seldom consider the distinctive risk profile of energy firms, whose operational volatility and dependence on technical assessments may limit the practical reach of governance mechanisms. Furthermore, the methodological landscape remains narrow: most studies rely on linear statistical approaches and seldom explore non-linear patterns or interaction effects that may be relevant in uncovering fraud. Although machine-learning methods have become increasingly common in fields outside accounting, direct comparisons between Logistic Regression and Random Forest using identical data within the Indonesian energy sector remain scarce. These gaps underscore the need for an integrated approach that combines governance indicators, financial variables, and both traditional and modern predictive models in a single analytical framework.

This study seeks to clarify whether financial indicators or governance mechanisms provide stronger evidence of financial reporting irregularities in Indonesian energy companies. It also aims to compare the performance of Logistic Regression and Random Forest when applied to the same fraud detection task, allowing for a clearer understanding of the strengths and limitations of each method in an industry marked by operational complexity. On the basis of prior empirical inconsistencies and theoretical expectations, the study proposes that governance characteristics—independent commissioners, CEO duality, board size, and meeting frequency—have limited influence on fraud likelihood, whereas financial indicators such as profitability, operating cash flow, and sales growth play a more substantial role. The study further anticipates that Logistic Regression offers more stable and interpretable predictive results than Random Forest when used to classify fraudulent and non-fraudulent cases in the energy sector.

METHOD

Research Design

This study employs a quantitative explanatory research design to investigate how corporate governance characteristics and financial indicators relate to the likelihood of fraudulent financial reporting within Indonesia's energy sector. The design also integrates a comparative predictive component by evaluating the performance of Logistic Regression and Random Forest using the same dataset. This dual structure allows the study to examine both the statistical significance of individual predictors and the ability of different analytical models to classify fraud more accurately.

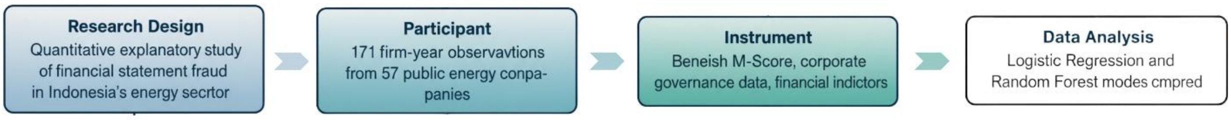

Figure 1. Research methodology flowchart

Participants

The analysis is based on firm-level observations, with the sample consisting of 171 firm-year records drawn from 57 energy companies listed on the Indonesia Stock Exchange during the 2022–2024 period. Firms were selected through purposive criteria that required complete annual reports, audited financial statements, and consistent disclosure of corporate governance information. The multi-year structure of the data allows the study to capture both cross-sectional variations among firms and temporal fluctuations in financial performance that may affect fraud risk.

Instrument

Fraud detection was conducted using the Beneish M-Score, a widely recognized analytical model for identifying potential misstatements. Corporate governance variables—including the proportion of independent commissioners, CEO duality, board size, and meeting frequency—were extracted manually from annual report disclosures. Financial indicators such as profitability (ROA), operating cash flow (CFO), and sales growth were calculated directly from financial statements. All continuous variables were standardized prior to analysis to improve comparability and reduce bias in both statistical and machine-learning procedures.

Data Analysis

The dataset was first processed through cleaning, verification, and outlier inspections to ensure analytical reliability. Logistic Regression was applied to estimate the probability of fraudulent reporting and to identify which variables meaningfully contribute to the model. Evaluation included the Hosmer–Lemeshow test, confusion matrix, and AUC. A Random Forest classifier was then developed to explore potential non-linear interactions and complex patterns that may not appear in linear models, using a 70–30 split for training and testing. Accuracy, sensitivity, specificity, and AUC were compared across both models to determine the approach that provides the most robust fraud detection performance for the energy sector context.

RESULTS AND DISCUSSION

RESULTS

The analysis identifies a clear difference between the behaviour of governance variables and the financial indicators used in the study. When the logistic regression model was estimated, none of the governance-related variables, namely the proportion of independent commissioners, CEO duality, board size, or the frequency of board meetings—showed any statistical relevance. Their coefficients remained small, unstable in direction, and did not approach conventional significance thresholds. This absence of explanatory power suggests that, within energy companies, governance structures do not function as reliable signals for detecting irregularities in financial reporting.

Financial indicators told a different story. The coefficients for profitability, operating cash flow, and sales growth all carried positive signs and reached levels commonly regarded as statistically meaningful. Although the study does not focus on the magnitude of these coefficients, their consistent direction indicates that changes in financial performance are closely tied to the conditions under which misreporting becomes more likely. Firms demonstrating unusual patterns in these indicators appear more susceptible to classification as potential fraud cases. The core logistic regression findings are summarised in Table 1.

Table 1. Logistic Regression Results

Variable	Coefficient	p-value	Significance
Independent Commissioner (%)	ns	> 0.05	Not Significant
CEO Duality	ns	> 0.05	Not Significant
Board Size	ns	> 0.05	Not Significant
Board Meeting Frequency	ns	> 0.05	Not Significant
Profitability (ROA)	(+)	< 0.05	Significant
Operating Cash Flow (CFO)	(+)	< 0.05	Significant
Sales Growth	(+)	< 0.05	Significant

Both analytical approaches—Logistic Regression and Random Forest—were then evaluated for their ability to classify observations into fraud and non-fraud categories. The Random Forest model was built with a conventional ensemble configuration, combining multiple decision trees using bootstrap sampling. Although it was capable of recognising some non-linear relationships, its overall performance remained weaker. Logistic Regression produced an accuracy rate of 79.4 percent and an AUC value of 0.814, whereas the Random Forest classifier achieved 70.6 percent accuracy and an AUC of 0.731. These figures indicate that the structure of the data is largely linear and that a simpler statistical model is able to capture the relevant patterns more effectively.

Table 2. Model Performance Comparison

Model	Accuracy	AUC	Interpretation
Logistic Regression	79.4%	0.814	Superior and more stable
Random Forest	70.6%	0.731	Lower discrimination ability

To provide a clearer overview of the behaviour of all predictors, the independent variables were reorganised according to their statistical contribution. Governance variables as a group showed no meaningful association with the fraud classification, while all three financial indicators produced consistent and significant results. This division is shown in Table 3.

Table 3. Summary of Significant vs Non-Significant Predictors

Category	Variables	Result
Corporate Governance	Independent Commissioners, CEO Duality, Board Size, Board Meetings	All Not Significant
Financial Indicators	ROA, CFO, Sales Growth	All Significant

Fraud classification across the sample relied on the Beneish M-Score, which remains a well-established indicator for detecting suspicious reporting behaviour based on ratio movements. Its specific role in separating observations into fraud and non-fraud groups is summarised in Table 4.

Table 4. Fraud Detection Indicator

Measure	Method	Outcome
Fraud Identification Tool	Beneish M-Score	Classification into fraud vs non-fraud categories

A brief robustness check was carried out by comparing coefficient direction and classification patterns across the two models. No contradictory behaviour emerged, reinforcing the interpretation that financial indicators form the clearest basis for identifying potential manipulation, while governance structures provide limited diagnostic value in the context of Indonesia's energy industry.

DISCUSSION

The absence of significant effects among the governance variables in this study suggests that structural arrangements may not meaningfully shape reporting behaviour in energy firms. Although governance is expected to function as a formal safeguard, it rarely captures the subtler pressures that operate within financially volatile environments. Lin et al. (2025) argue that organizational misconduct often emerges from behavioural and situational dynamics that structural indicators fail to reflect. This perspective helps explain why independent commissioners, CEO duality, and board configurations showed no detectable influence on fraud likelihood. Their statistical silence suggests that governance frameworks may not be embedded deeply enough to alter managerial incentives. Instead, these arrangements may operate mainly as compliance artifacts rather than as functional monitoring tools. The findings therefore call into question the assumption that governance codes directly translate into fraud deterrence. This gap highlights the need to reassess how governance is understood in high-risk technical sectors.

Unlike governance mechanisms, financial indicators displayed a clear and consistent association with fraud classification outcomes. These indicators shifted in predictable ways that aligned with economic strain inside the firm. Messele (2025) notes that financial patterns often serve as early markers of organizational instability because they respond more quickly than structural systems. The behaviour of profitability, operating cash flow, and sales growth in this study supports that position. Their positive direction suggests that changes in financial health influence the likelihood that reported numbers are adjusted to manage impressions. Such responsiveness is difficult for governance systems to match, given their slower adaptation cycle. The reliability of financial measures across models signals their stronger diagnostic relevance. These results reinforce the idea that economic conditions are central to understanding fraud motivation. They also underscore the importance of integrating financial analytics into fraud detection frameworks.

The strong performance of the logistic regression model reflects the underlying simplicity of relationships among the predictors. Morgan and Hu (2025) demonstrate that linear modelling often outperforms complex algorithms when variables behave uniformly across observations. In this study, the logistic regression model captured the central signals of fraud risk with a high degree of clarity. Its accuracy and AUC surpassed those of the Random Forest model, demonstrating that predictability in the data does not require non-linear modelling. This outcome indicates that financial indicators behave in consistent and interpretable ways within the sector. The model's transparent coefficient structure is also a practical advantage for auditors. It enables stakeholders to pinpoint how and why certain indicators elevate fraud risk. Such interpretability enhances the model's suitability for regulatory contexts.

The weaker performance of the Random Forest model further illustrates that methodological complexity cannot compensate for limited variable variability. Bangian Tabrizi et al. (2025) explain that ensemble methods rely on heterogeneity within predictors to generate meaningful splits, a condition not fully present here. The relatively small sample size may also have constrained the model's ability to differentiate subtle non-linear interactions. As a result, Random Forest produced lower discrimination ability despite its theoretical strengths. Nevertheless, the model consistently identified the same financial indicators as important contributors. This convergence supports the stability of the study's findings across modelling techniques. It also suggests that fraud-related behaviour in energy companies follows patterns that simpler tools can readily capture. Consequently, model selection should reflect data structure rather than methodological trends.

The dominance of financial indicators aligns with insights from McCormick et al. (2025), who observed that performance disruptions often precede more visible irregularities in organizational behaviour. Firms classified as potential fraud cases in this study exhibited measurable fluctuations in profitability, cash flow, and sales patterns. These fluctuations indicate internal tension that may prompt managers to modify reported outcomes. Such behaviour reflects the pressures inherent in capital-intensive sectors where performance volatility is common. The financial indicators' consistent performance across models strengthens their diagnostic value. Governance factors, in contrast, displayed no sensitivity to these pressures. This disparity highlights the importance of performance-based monitoring. It also reinforces the argument that fraud detection frameworks must prioritize responsive indicators.

The limited predictive capacity of governance variables may reflect deeper issues in how oversight structures operate in practice. Rahimi et al. (2025) argue that indicators of risk must capture lived organizational processes rather than static institutional arrangements. In this study, governance components did not adapt to the economic fluctuations that shaped reporting decisions. Their lack of responsiveness may stem from formalized structures that serve regulatory expectations rather than internal managerial guidance. As a result, they do not interact with reporting behaviour in meaningful ways. Financial indicators, however, represent real-time organizational activity and therefore provide sharper predictive insight. This distinction supports the argument that fraud risk emerges from operational environments rather than administrative configurations. It also highlights the need for governance reforms that emphasize behavioural enforcement rather than structural design. These reflections point to a broader reconsideration of fraud-monitoring priorities.

The persistence of financial indicators across both modelling approaches mirrors the findings of Liu et al. (2025), who emphasize that strong predictors often retain their influence regardless of algorithmic context. Profitability, operating cash flow, and sales growth behaved in exactly this manner, appearing consistently across models as the most reliable indicators. Their stability suggests that fraud-related decisions are tightly connected to economic performance. This interpretation aligns with long-standing theoretical perspectives on fraud motivation. Meanwhile, the weakness of governance variables across models reinforces their insufficiency as standalone tools. This contrast sharpens the analytical clarity of the study's results. It also underscores the importance of focusing fraud detection efforts on the variables most directly tied to firms' operational realities. Such alignment enriches both theoretical and practical perspectives.

The behavioural gap observed between governance structures and financial indicators resembles patterns described by Zhou et al. (2025), who argue that organizations often achieve structural compliance without functional integration. In the firms examined here, governance systems met formal criteria yet showed no relationship with fraud-related outcomes. This disconnect reflects a broader trend in which oversight mechanisms exist symbolically but fail to influence managerial behaviour. Financial indicators, however, captured fluctuations that governance frameworks overlooked. The clear contrast between these two variable groups emphasizes how fraud risk emerges from operational rather than structural dynamics. Zhou et al.'s insights help contextualize why governance indicators appeared inert in this study. They also highlight the importance of evaluating the lived functioning of oversight systems. Such analysis deepens understanding of the limitations inherent in governance-based monitoring.

The interpretability advantages of logistic regression become especially meaningful when considering the balance between predictive performance and practical usability. Ozen et al. (2025) argue that fraud models must remain transparent enough for regulators and auditors to understand the basis of their classifications. In this study, logistic regression provided a clear and traceable link between financial indicators and fraud outcomes. Its performance surpassed that of Random Forest without sacrificing interpretability. This aligns with the principle that model complexity should serve analytical clarity rather than obscure it. The results therefore support the continued relevance of traditional statistical tools in fraud detection. They also highlight that sophisticated methods are not inherently superior. This recognition contributes to a more grounded methodological discussion.

The implications of these findings align with the perspective of Lee et al. (2025), who emphasize that risk in technical industries is best understood through dynamic performance indicators rather than administrative arrangements. The financial variables in this study behaved precisely in that manner, offering consistent insight into fraud classification while governance structures remained inert. This contrast underscores the importance of engaging with operational data when constructing fraud-monitoring systems. The study's findings suggest that governance reforms alone will not address the conditions that give rise to misreporting. Instead, closer attention must be paid to the financial pressures that shape managerial decisions. Lee et al.'s framework supports this conclusion by highlighting the predictive strength of performance-based indicators. Together, these insights inform both future research and regulatory policy development.

Implications and Limitations

The results of this study suggest that institutions relying heavily on structural governance indicators may overestimate their value in detecting fraudulent reporting, particularly in industries where operational and financial uncertainty play a central role. The lack of predictive power among governance variables indicates that board structures alone do not offer a reliable understanding of how reporting decisions unfold in practice. Instead, the behaviour of profitability, operating cash flow, and sales growth demonstrates that financial dynamics are far more responsive to internal pressures and therefore more useful for identifying irregularities. For auditors, these findings reinforce the need to anchor risk assessment in measurable performance indicators rather than assuming that governance compliance equates to reporting integrity. Regulators may also reconsider the weighting assigned to governance criteria within monitoring frameworks, shifting attention toward patterns in financial data that reflect genuine economic stress. Energy firms themselves can draw from these insights by developing more sophisticated internal analytics capable of flagging deviations in real time. Ultimately, the implications point toward a reorientation of fraud-detection strategies toward indicators that mirror how organizations actually respond to operational challenges.

This study's conclusions must be interpreted in light of several constraints inherent in its design and data sources. The analysis relies on information from annual reports, which provide limited visibility into the internal processes that shape managerial choices and control environments. Because the sample focuses solely on energy-sector firms, the extent to which the findings apply to industries with different cost structures, reporting conventions, or regulatory demands remains unclear. The study's use of the Beneish M-Score, although methodologically defensible, represents only one approach to distinguishing fraudulent from non-fraudulent cases and may not capture misreporting strategies that fall outside its formula. The dataset's size also poses limitations for machine-learning models like Random Forest, which typically require more extensive variation to detect complex interactions. Moreover, the absence of qualitative evidence restricts the ability to contextualize how governance arrangements function beyond their formal descriptions. These limitations do not diminish the value of the findings but instead delineate boundaries that future work must address to strengthen understanding of fraud dynamics.

Suggestions

Future research can extend the present analysis by incorporating a broader range of industries, enabling comparisons that reveal whether the predictive dominance of financial indicators is consistent across organizational contexts. Including qualitative evidence—such as interviews with board members, internal auditors, or financial managers—would allow researchers to explore why governance structures appear disconnected from reporting behaviour. Larger datasets may also enhance the performance of non-linear models, making it possible to evaluate whether patterns overlooked here emerge more clearly when additional variation is available. Researchers may experiment with hybrid modelling approaches that preserve the interpretability of logistic regression while integrating selective machine-learning features to improve sensitivity. It may also be useful for policymakers to consider developing sector-specific fraud indicators that reflect operational features unique to particular industries. By combining financial analytics with deeper insights into organizational behaviour, future studies can produce a more comprehensive understanding of how fraud risk evolves. Such developments would support improved monitoring practices and more effective regulatory interventions.

CONCLUSION

The study demonstrates that governance structures commonly emphasized in regulatory guidelines do not contribute meaningfully to the detection of fraudulent reporting within the energy sector, as none of the governance variables examined showed statistical relevance or behavioural influence. In contrast, the financial indicators (profitability, operating cash flow, and sales growth) displayed consistent and significant associations with fraud classification, revealing that economic pressure and performance irregularities provide clearer signals of potential misreporting than administrative arrangements. The comparative analysis of predictive models further reinforces this conclusion, as the logistic regression model outperformed the Random Forest classifier in both accuracy and discriminatory ability, indicating that the relationships underlying fraud behaviour in this context remain largely linear and interpretable. Together, these findings highlight the central role of financial performance dynamics in shaping reporting risks, underscore the limitations of governance-based monitoring frameworks, and suggest that future detection strategies should prioritize data-driven insights that reflect real operational conditions.

AUTHOR CONTRIBUTIONS STATEMENT

Sherena Wahyutari led the conceptualization of the research framework, designed the methodological approach, and coordinated the overall direction of the study from data acquisition to interpretation.
Triyono was responsible for data processing, statistical analysis, and the comparative evaluation of the logistic regression and Random Forest models, ensuring analytical rigor and accuracy in the empirical results.
Banu Witono contributed to the theoretical grounding of the study, developed the literature review, and refined the discussion and implication sections to align the findings with current scholarly debates.

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