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The FDP Mirror Framework for Financial Statement Fraud Risk Assessment: Integrating Deterrence and Analytical Detection

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ABSTRACT

Financial statement fraud remains a persistent challenge for auditors, particularly in environments with weak deterrence and complex financial disclosures. Auditing standards such as ISA 240 require auditors to integrate professional scepticism, fraud risk assessment, and analytical procedures. However, conventional audit approaches often treat behavioural deterrence assessment and analytical detection as separate considerations. This study empirically evaluated the Fraud Deterrence Propeller Mirror (FDP Mirror) as an applied audit framework that integrated deterrence maturity assessment with analytical procedures for financial statement fraud risk assessment. Using data from corporate entities and public sector organisations in Indonesia, PLS-SEM was employed to assess deterrence maturity, while logistic regression and machine learning techniques were used to evaluate fraud detection performance. The findings indicated that stronger deterrence maturity was associated with improved governance integrity, while hybrid analytical models combining financial indicators, anomaly testing, and narrative analysis demonstrated stronger fraud detection capability than conventional assessment approaches. The results suggested that fraud risk assessment was strengthened when behavioural governance conditions and analytical evidence are evaluated jointly. This study contributes to auditing literature by extending the practical interpretation of ISA 240 and enhancing the integration of behavioural governance assessment and analytical procedures in fraud risk assessment.

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1. INTRODUCTION

Financial statement fraud remains a persistent audit challenge because material misstatements may be concealed within formally compliant reporting. In environments with uneven governance and enforcement, fraudulent reporting is not merely a technical irregularity but a behavioural and institutional phenomenon shaped by incentives, ethics, internal controls, and management conduct (Singleton et al., 2016; Albrecht et al., 2018; Gkegkas et al., 2025). For auditors, this creates practical difficulties because conventional fraud risk assessment often relies heavily on observable financial indicators while giving less systematic attention to the behavioural conditions that make fraud more likely.

Auditing standards explicitly recognise this challenge. SA 240, aligned with ISA 240, requires auditors to maintain professional scepticism, identify fraud risk factors, and apply analytical procedures to detect material misstatements arising from fraud (IAASB-ISA, 2025; SPAP SA 240 Rev 2021, 2021). SA 315 / ISA 315 further requires auditors to develop an understanding of the entity's governance environment, internal controls, and risk conditions as part of risk assessment procedures (IAASB-ISA, 2019; SPAP SA 315 Rev 2021, 2021). Although these standards provide a robust foundation, implementation remains challenging because fraud increasingly manifests through managerial judgement, selective disclosure, and narrative manipulation not always captured through conventional procedures (Hammersley, 2011).

Fraud analytics have expanded the tools available to auditors. Financial ratio models such as Beneish M Score and F Score identify potential earnings manipulation and misstatement risk (Beneish, 1999; Dechow et al., 2011). Benford's Law has been applied to detect anomalous numerical distributions that may indicate irregular transactions, particularly in expenditure-intensive environments (Durtschi et al., 2004). More recent studies have applied Natural Language Processing to analyse management narratives, showing that linguistic tone and disclosure inconsistency may provide fraud-related signals (Humpherys et al., 2011; Chen et al., 2017; Devlin et al., 2019; A. A. Ali et al., 2023). While these approaches strengthened analytical detection, they were typically applied as isolated procedures rather than within an integrated fraud risk assessment architecture.

This separation created an important limitation in audit practice. Analytical indicators may reveal anomalies, but interpretation weakens when detached from governance conditions. Likewise, governance assessments may identify weak controls without structured analytical evidence for fraud evaluation. Prior studies on fraud deterrence have emphasised that ethical discipline, reinforcement, enforcement credibility, and organisational vigilance influenced the conditions under which fraud emerged or was discouraged (Koerniawan et al., 2022; Koerniawan, 2024; Koerniawan et al., 2024c). However, deterrence maturity has rarely been operationalised as a structured component of auditors' fraud risk assessment procedures.

This study addressed that limitation by empirically evaluating the Fraud Deterrence Propeller Mirror (FDP Mirror) Framework as an integrated audit approach to financial statement fraud risk assessment. The framework combines deterrence maturity assessment with analytical procedures, allowing interpretation of fraud indicators within a governance context. The empirical design combines behavioural evidence, financial analytics, anomaly detection, narrative analysis, logistic modelling, and machine learning classification. The study was situated in Indonesia's public accountability environment, where governance, oversight, and reporting accountability interacted within a unified assurance setting.

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This study integrated behavioural deterrence and analytical fraud detection within an audit framework, extending the practical interpretation of ISA 240 and ISA 315 through the FDP Mirror Framework.

2. LITERATURE REVIEW

Fraud in financial reporting has long been recognised as a behavioural and organisational phenomenon rather than a purely technical accounting issue. Prior studies have shown that fraud risk emerges from the interaction of incentives, opportunities, and rationalisation, which are strongly influenced by ethical climate, internal controls, and enforcement credibility (Singleton et al., 2016; Albrecht et al., 2018). In audit contexts, weak deterrence environments reduced compliance discipline and increased tolerance for opportunistic reporting behaviour. This created an unresolved challenge in audit practice, as fraud risk assessment often depended on analytical evidence while the behavioural conditions that shaped reporting conduct were assessed less systematically.

The Fraud Deterrence Propeller (FDP), also referred to as the DETER-E model, conceptualises fraud deterrence as a multidimensional governance mechanism shaped by ethical discipline, due diligence, transparency orientation, reinforcement, and enforcement actions (Koerniawan et al., 2022; Koerniawan, 2024; Koerniawan et al., 2024c). Rather than treating deterrence as a static element of internal control, the FDP framework emphasised how deterrence maturity influenced organisational behaviour and reporting discipline. Empirical evidence from Southeast Asian settings suggests that stronger deterrence maturity is associated with improved governance integrity and reduced vulnerability to financial misrepresentation (Arifin & Koerniawan, 2025; Koerniawan et al., 2024b, 2024c, 2025a). However, despite its governance relevance, deterrence maturity has rarely been operationalised as a structured component of audit fraud risk assessment. Building on this behavioural deterrence foundation, the present study extended the original FDP concept by examining how deterrence maturity may be systematically integrated into audit fraud risk assessment.

Auditing standards reinforced the relevance of deterrence to fraud risk assessment. ISA 240 acknowledges that fraud risk is shaped not only by financial incentives but also by behavioural norms and organisational conditions, requiring auditors to apply professional scepticism and analytical procedures (IAASB-ISA, 2025; SPAP SA 240 Rev 2021, 2021). These requirements are complemented by ISA 315, which emphasised understanding the control environment and governance structures as part of risk identification (IAASB-ISA, 2019; SPAP SA 315 Rev 2021, 2021). Audit judgement research has further indicated that auditors' fraud risk assessments were sensitive to behavioural cues related to management integrity and control strength, and that failure to recognise such cues increases the likelihood of undetected misstatements (Hammersley, 2011). Yet, existing audit practice provides limited guidance on how behavioural governance evidence should be systematically integrated with analytical fraud assessment.

Alongside behavioural governance research, fraud detection studies have developed a range of analytical procedures to identify irregularities in financial reporting. Financial ratio-based models such as the Beneish M Score and the F Score have been widely used to detect earnings manipulation and accrual-based misrepresentation (Beneish, 1999; Dechow et al., 2011). Benford's Law has been applied to identify abnormal digit patterns in accounting data, particularly in public sector contexts where expenditure manipulation may occur (Durtschi et al., 2004). More recent research has highlighted the role of narrative disclosures in fraud detection. Studies using Natural Language Processing have demonstrated that biased

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tone, selective emphasis, and linguistic inconsistency in managerial narratives were associated with opportunistic reporting behaviour (Humpherys et al., 2011; Chen et al., 2017; Devlin et al., 2019; A. A. Ali et al., 2023).

While these analytical tools improved detection capability, they were commonly applied as standalone procedures. This has created an important limitation because analytical anomalies do not always distinguish between genuine fraud risk and governance environments characterised by weak controls, managerial discretion, or poor ethical discipline. As a result, auditors may detect red flags without a sufficiently structured behavioural framework for interpretation. The FDP Mirror Framework was proposed to address this limitation by integrating deterrence maturity assessment with analytical fraud procedures, allowing fraud indicators to be interpreted within a broader governance context.

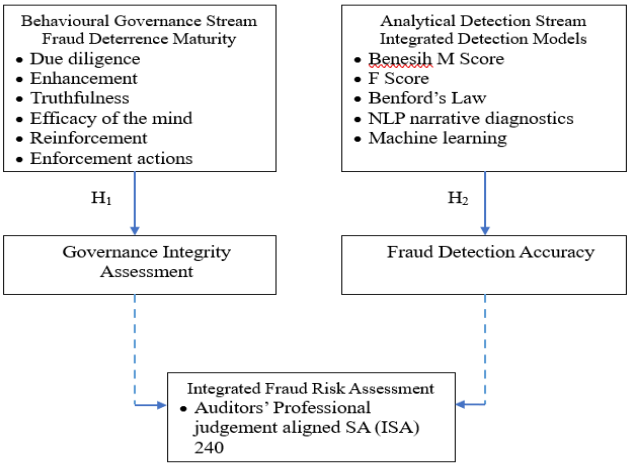

Fig. 1. Conceptual Architecture of the FDP Mirror Framework

Source: Developed by the author based on FDP theory

Figure 1 illustrates the conceptual architecture of the FDP Mirror Framework. The framework combines behavioural governance assessment through fraud-deterrence maturity, which informs governance integrity assessment, with analytical fraud detection using financial, anomaly-based, and narrative diagnostics. Together, these evidence streams suggest the value of an integrated audit approach in which behavioural governance assessment and analytical fraud detection jointly inform auditors' professional judgement in assessing financial statement fraud risk under ISA 240. Accordingly, this study advanced two hypotheses:

H1: Stronger fraud deterrence maturity is positively associated with improved governance integrity within organisations.

H2: Fraud detection models integrating financial ratios, anomaly testing, and narrative analysis achieve higher detection accuracy than conventional fraud risk assessment approaches.

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3. METHODOLOGY

3.1 Research Design

This study adopted an applied empirical research design to evaluate the FDP Mirror as an integrated framework for fraud risk assessment. The design combined behavioural governance analysis and analytical detection techniques in accordance with auditing standards related to fraud consideration and risk assessment. The methodological approach was aligned with applied accounting and auditing research that seeks to support professional judgement through empirical evidence.

3.2 Sample Selection and Data Collection

The study used mixed datasets drawn from both corporate and public sector environments. Financial statement data consisted of annual reports of listed state-owned and non-state-owned enterprises for the period 2018 to 2023. The corporate sample focused on strategically significant entities operating within Indonesia's public accountability environment, including state-affiliated entities subject to external public audit oversight. Public sector data included audited Local Government Financial Statements from selected provinces in Java for the period 2019 to 2023. Java was selected because it represented the largest concentration of economic activity, public expenditure, and administrative governance in Indonesia. Narrative disclosures were extracted from the Management Discussion and Analysis sections and public accountability documents.

Behavioural data were collected using the validated Fraud Deterrence Propeller (FDP Mirror) Protocol administered through purposive sampling to auditors from the Supreme Audit Institution and internal government audit bodies with a minimum of ten years of audit experience. These datasets enabled integrated analysis of governance conditions, numerical indicators, and narrative disclosure behaviour (Cressey, 1953; Coetzee, 2016; Choi & Lee, 2018; Koerniawan et al., 2022; A. A. Ali et al., 2023).

3.3 Model Specification

Two complementary empirical models were specified. The first model examined the relationship between fraud deterrence maturity and governance integrity using PLS-SEM. This approach was appropriate for analysing multidimensional behavioural constructs and assessing structural relationships in applied governance research (Nunnally, 1978; Hair et al., 2022; Ghozali, 2023).

The second model evaluated fraud detection performance using logistic regression and machine learning classifiers, including Random Forest, Gradient Boosting, and Neural Network models. Detection accuracy was assessed using standard classification metrics such as accuracy, precision, recall, and Receiver Operating Characteristic curves (Hosmer et al., 2013; Nassif et al., 2021; Hernandez Aros et al., 2024).

The FDP Mirror Framework was conceptualised as an integrated audit decision architecture rather than a single linear causal model. Accordingly, complementary methods were employed to reflect the distinct nature of the constructs examined. For H1, PLS-SEM was appropriate because fraud deterrence maturity and governance integrity are multidimensional latent constructs measured through behavioural indicators (Hair et al., 2022). In contrast, H2 evaluated observable fraud-related indicators and classification performance, making logistic regression and machine learning approaches more appropriate for predictive

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fraud detection (Hosmer et al., 2013). Integration occurre at the level of auditors' professional judgement under SA 240 / ISA 240 rather than as an additional empirically tested causal hypothesis.

The structural and predictive models were specified as follows:

For H1:

$$GI = \beta_0 + \beta_1 FDM + \varepsilon \quad (1)$$

where *GI* denoted governance integrity, *FDM* denoted fraud deterrence maturity, β coefficients represented estimated parameters, and ε was the error term.

For H2:

$$P(Fraud = 1) = \frac{1}{1+e^{-(\alpha+\beta_1 MSCORE+\beta_2 FSCORE+\beta_3 BENFORD+\beta_4 NLP)}} \quad (2)$$

where *P(Fraud=1)* denoted the predicted probability of fraud classification, *MSCORE* represented Beneish M-Score, *FSCORE* represented Dechow F-Score, *BENFORD* denoted anomaly indicators derived from Benford's Law, *NLP* captured narrative disclosure diagnostics, and α and β denoted estimated model parameters.

3.4 Analytical Techniques

Behavioural governance analysis was conducted using PLS-SEM to test the relationship specified in H1. Fraud detection analysis corresponding to H2 was conducted using logistic regression and machine learning techniques to compare the performance of integrated analytical models with conventional assessment approaches. Narrative disclosure analysis within this stream employed transformer-based BERT sentiment classification to identify linguistic tone distortion and selective disclosure patterns relevant to fraud risk assessment. This dual analytical strategy enabled parallel evaluation of behavioural deterrence and analytical detection within the FDP Mirror framework.

4. RESULTS AND DISCUSSION

4.1 Data Collection and Descriptive Overview

This study employed a multi-source dataset comprising financial statements, narrative disclosures, and behavioural survey data. Financial data included annual reports of listed state-owned and non-state-owned enterprises for the period 2018 to 2023, while public sector data consisted of audited Local Government Financial Statements from selected regions in Java covering 2019 to 2023. These datasets supported ratio-based analysis, anomaly testing, and narrative evaluation in line with prior fraud detection research (Pourhabibi et al., 2020; A. A. Ali et al., 2023; Koerniawan et al., 2024b).

Narrative data were extracted from the management discussion and analysis sections and public accountability documents. Behavioural data were collected using the Fraud Deterrence Propeller Protocol, administered to auditors from external and internal government audit institutions with a minimum of ten years of audit experience (Koerniawan et al., 2022, 2024c, 2025a). Table 1 summarises the datasets employed in this study. The institutional setting reflected Indonesia's public accountability architecture, in

which external audit oversight extended to both public-sector reporting entities and strategically significant state-affiliated enterprises

Table 1. Dataset Collected

Data Source	Data Type	Number of Observations	Remarks
SOEs and strategically significant enterprises	Financial Statements (2018–2023)	50 entities	Corporate fraud analytics sample
Local Governments in Java	Audited Financial Statements (LKPD) (2019–2023)	20 reports	Public sector anomaly dataset
Corporate disclosures	MD&A Narratives	250 documents	NLP dataset
BPK and BPKP Auditors	FDP Protocol survey and interviews	63 respondents	Purposive sample, minimum 10 years of audit experience

Source: Author's compilation (2025)

4.2 Validation of Fraud Deterrence Maturity

Psychometric testing confirmed the reliability and validity of the Fraud Deterrence Propeller Protocol as a behavioural governance instrument. The measurement model demonstrated strong internal consistency and construct reliability, with Cronbach's Alpha of 0.876, composite reliability of 0.912, and average variance extracted of 0.634, exceeding recommended thresholds for behavioural construct assessment (Nunnally, 1978; Hair et al., 2022; Ghozali, 2023). Discriminant validity was also satisfactory, with a Heterotrait–Monotrait Ratio of 0.682, indicating acceptable construct separation.

Exploratory Factor Analysis identified six dominant dimensions consistent with the theoretical structure of the deterrence framework, namely due diligence, enhancement, truthfulness, efficacy of mind, reinforcement, and enforcement actions (Koerniawan et al., 2022; Koerniawan, 2024; Koerniawan et al., 2024b, 2024c, 2025a).

These dimensions reflected key behavioural mechanisms underpinning fraud deterrence, including ethical discipline, procedural compliance, cognitive preparedness, and enforcement credibility. The scree plot presented in Figure 2 supported the retention of six factors, reinforcing construct validity.

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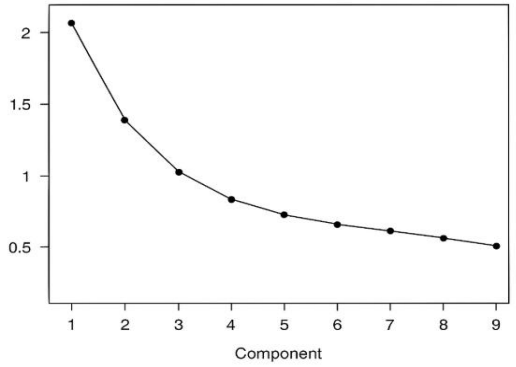

Fig 2. Scree Plot of EFA FDP Protocol

Qualitative feedback from auditors further indicated that deterrence effectiveness depends more on leadership integrity and enforcement consistency than on formal controls alone. These findings supported prior research emphasising the behavioural foundations of fraud prevention and governance integrity (Cheung, 2013; Arifin & Koerniawan, 2025; Mabel et al., 2025).

4.3 Results of Fraud Detection Models

Fraud detection analysis integrated numerical indicators, digit distribution testing, and narrative diagnostics to identify financial reporting risk. Consistent with prior studies, the Beneish M-Score identified a subset of observations exhibiting characteristics associated with potential earnings manipulation (Beneish, 1999; Dechow et al., 2011). F-Score analysis indicated that 12 of 50 observations exceeded the elevated manipulation threshold. The application of Benford's Law to public sector expenditure data revealed statistically significant digit deviations, indicating potential irregularities linked to control weaknesses (Durtschi et al., 2004).

Narrative analysis using Natural Language Processing identified tone distortion and selective disclosure patterns in both corporate and public sector reports. The transformer-based model achieved classification accuracy consistent with prior empirical evidence on narrative-based fraud detection (Humpherys et al., 2011; Chen et al., 2017; Devlin et al., 2019; Boulieris et al., 2024; Hernandez Aros et al., 2024).

The combined results indicated that integrated numerical and narrative indicators provided stronger fraud detection signals than reliance on isolated analytical procedures. Table 2 summarises the principal analytical findings.

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Table 2. Summary of FDP Mirror Detection Results

Model	Dataset Sample	Key Findings
Beneish M Score	50 SOEs and strategically significant enterprises	12 per cent indication of potential earnings manipulation
F Score	50 SOEs and strategically significant enterprises	12 observations exceeded the fraud risk threshold, indicating elevated accrual-based manipulation risk
Benford's Law	20 LKPD reports	Significant digit deviations ($\chi^2 = 45.21$; $p < 0.01$)
NLP BERT Sentiment	250 MD&A documents	Accuracy 78 per cent (precision 0.74; recall 0.77)

Source: Author's analysis (2025)

4.4 Hypothesis Testing Results

Fraud Deterrence and Governance Integrity (H1)

Hypothesis H1 was tested using PLS-SEM. Structural model results indicated that fraud deterrence maturity had a positive and statistically significant effect on governance integrity ($\beta = 0.482$; $t = 6.234$; $p < 0.001$), supporting the proposed hypothesis. The model explained 42.7 per cent of the variance in governance integrity ($R^2 = 0.427$), with substantial effect size ($f^2 = 0.746$) and acceptable predictive relevance ($Q^2 = 0.283$).

Table 3. Summary of Hypothesis Testing Results

Hypothesis	Description	Key Method	Main Findings	Decision
H_1	Fraud deterrence maturity → governance integrity	SEM-PLS	$\beta = 0.482$; $t = 6.234$; $p < 0.001$; $R^2 = 0.427$; $f^2 = 0.746$; $Q^2 = 0.283$	Supported
H_2	Integrated fraud analytics → fraud detection accuracy	Logistic Regression & ML	Accuracy up to 87.3%; ROC-AUC = 0.91	Supported

Source: Author's analysis (2025).

Analytical Fraud Detection Performance (H2)

Hypothesis H2 examined whether integrated analytical models improve fraud detection accuracy. Logistic regression results indicated that financial and narrative indicators jointly contributed to fraud risk classification.

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Table 4. Predictive Performance of Analytical Fraud Detection Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	81.2%	0.78	0.75	0.76	0.84
Random Forest	85.5%	0.82	0.85	0.83	0.89
Gradient Boosting	83.1%	0.80	0.79	0.79	0.86
Neural Network (MLP)	81.9%	0.79	0.77	0.78	0.85
Integrated Best Model	87.3%	0.84	0.88	0.86	0.91
Conventional Auditor Judgement (Baseline)	69.4%	0.65	0.62	0.63	0.71

Source: Author's analysis (2025).

As shown in Table 4, the integrated best model achieved the highest predictive performance, with an accuracy of 87.3 per cent and a Receiver Operating Characteristic value of 0.91, indicating strong discriminatory capability. Random Forest, Gradient Boosting, and Neural Network models also outperformed conventional auditor judgement, while logistic regression demonstrated comparatively robust baseline classification performance. Confusion matrix analysis further identified 42 true positive and 104 true negative classifications, with limited false classifications, supporting the robustness of the integrated analytical approach. These findings suggested that machine learning-assisted analytical procedures provided stronger fraud risk classification capability than conventional judgement-based assessment, consistent with prior fraud analytics research (Hosmer et al., 2013; James et al., 2021; A. Ali et al., 2022).

The findings confirmed that hybrid models combining financial ratios, anomaly detection, and narrative analysis provided stronger detection signals than judgement-based approaches alone. These results aligned with auditing standards that emphasised analytical procedures as part of fraud risk assessment under SA 240 / ISA 240 (IAASB-ISA, 2025; SPAP SA 240 Rev 2021, 2021).

4.5 Integrated Interpretation

The combined results of H1 and H2 indicated that the FDP Mirror operated as an integrated framework linking behavioural deterrence and analytical detection. Stronger deterrence maturity supported governance integrity and reporting discipline, while enhanced analytical capability improved the identification of financial reporting risk.

This integrated perspective addressed a limitation in conventional fraud risk assessment, where analytical anomalies may lack behavioural context for interpretation. The present findings suggested that fraud signals become more meaningful when evaluated alongside governance conditions that shaped reporting conduct, managerial discretion, and organisational discipline. This interaction was consistent with

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the Fraud Theory, which conceptualised fraud as arising from the interaction of behavioural incentives, opportunities, and rationalisation processes (Cressey, 1953; Hammersley, 2011; Koerniawan, 2024).

From an audit perspective, the findings suggested that fraud risk assessment was strengthened when behavioural governance conditions were evaluated alongside numerical and narrative risk signals rather than in isolation. In this sense, the FDP Mirror Framework extended conventional analytical procedures by providing a structured interpretive layer for professional judgement (Mautz & Sharaf, 1961; FRC, 2022).

4.6 Discussion

The results demonstrated that conventional audit procedures may overlook important behavioural and narrative cues associated with fraud risk. While analytical tools such as financial ratios and digit tests provided valuable indicators, their effectiveness was enhanced when interpreted within a governance context characterised by deterrence maturity.

These findings supported prior evidence that ethical discipline, internal control strength, and enforcement enhance fraud prevention capability (Biegelman & Bartow, 2012; Abdul Aziz & Othman, 2021; Koerniawan et al., 2022, 2024c; Al Astal et al., 2026). From an audit perspective, behavioural deterrence maturity provided meaningful governance evidence for fraud risk assessment.

This finding highlighted a limitation in conventional fraud risk assessment, where analytical anomalies may lack behavioural context for interpretation (Hilal et al., 2022; Gkegkas et al., 2025). Fraud indicators become more meaningful when evaluated alongside organisational discipline and enforcement credibility.

In corporate environments, analytical indicators captured accrual manipulation and performance pressure, while narrative analysis revealed optimism bias and selective disclosure. In public sector contexts, digit deviations and narrative justification patterns reflected procedural gaps and reputational concerns. Despite these differences, both sectors exhibited similar risk dynamics when deterrence mechanisms were weak.

From an audit perspective, these findings reinforced SA 240 / ISA 240's requirement to combine professional scepticism, analytical procedures, and governance understanding. The FDP Mirror addressed limitations of isolated fraud detection models by integrating behavioural deterrence maturity with analytical diagnostics.

Although the empirical setting reflected Indonesia, the broader implication extended beyond this context. Fraud risk assessment became more robust when analytical evidence was interpreted within behavioural governance structures.

Overall, the findings supported the application of integrated behavioural and analytical approaches in fraud risk assessment and reinforced the relevance of analytical procedures under SA 240 / ISA 240 and related auditing standards.

5. CONCLUSION

The findings indicated that fraud risk assessment was strengthened when behavioural deterrence maturity was evaluated alongside analytical procedures rather than treated as separate audit considerations.

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Stronger deterrence maturity was associated with improved governance integrity, while integrated analytical models combining financial indicators, anomaly testing, and narrative analysis demonstrated stronger fraud detection capability than conventional judgement-based approaches. Analytical red flags became more informative when interpreted within governance environments characterised by ethical discipline, enforcement credibility, and effective controls.

This study should be interpreted within its empirical context. The analysis was grounded in Indonesia's public accountability environment, which may limit broader institutional generalisability. Future research may test the framework across broader institutional and cross-country audit settings.

Overall, the study contributes to auditing literature by positioning fraud risk assessment as both a behavioural and analytical audit challenge, extending the practical interpretation of ISA 240 through an integrated audit decision framework.

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7. CONFLICT OF INTEREST STATEMENT

The authors declare that this research was conducted in the absence of any personal, commercial, or financial conflicts of interest. The authors further declare that the funders had no role in the study design, data collection, analysis, interpretation of the results, or preparation of the manuscript.

8. AUTHORS' CONTRIBUTIONS

Koenta Adji Koerniawan: Conceptualisation, methodology, formal analysis, investigation, and writing-original draft, Supervision; **Hosam Alden Riyadh**: Conceptualisation, methodology, and formal analysis; **Galuh Tresna Murti**: Conceptualisation, formal analysis, and validation; **Arfive Gandhi**: Writing- review and editing, and validation. **Asrarul Rahman**: Writing-review and editing, investigation, formal analysis and translation; **Nungki Selviandro**: Writing-review and editing, validation, and translation; **Ferdio Ghifary Fidhien**: Writing-review and editing, methodology, and translation.

9. DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

During the preparation of this work, the authors used Grammarly in order to improve the readability and language quality of the work. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

10. DATA AVAILABILITY

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

11. ETHICS STATEMENT

The authors declare that this study was conducted in accordance with applicable ethical standards for research involving human participants. Participation in the FDP Protocol survey and interviews was voluntary, and informed consent was obtained from the participants. The anonymity and confidentiality of participants were maintained throughout the data collection, analysis, and reporting processes.

12. REFERENCES

Abdul Aziz, F. L., & Othman, I. W. (2021). Internal Auditors' Perception on the Efficacy of Fraud Prevention and Detection in the Public Sector. In *Universal Journal of Accounting and Finance* (Vol. 9, Issue 4, pp. 764–772). Horizon Research Publishing. https://doi.org/10.13189/ujaf.2021.090422

Al Astal, A. Y. M., Alnimer, R., Anto, M. L., Jawabri, A., Hani, L. Y. B., Samara, H. H. H., & Almansour, B. Y. (2026). The Impact of the Internal Control System Through the Committee of Sponsoring Organizations (COSO) Framework Toward Fraud Prevention in the Kingdom of Bahrain. In *Studies in Systems, Decision and Control* (Vol. 642, pp. 691–702). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/978-3-032-07220-7_61

Albrecht, W. S., Albrecht, C. C., Albrecht, C. O., & Zimbelman, M. F. (2018). *Fraud Examination* (6th ed.). Cengage Learning.

Ali, A. A., Khedr, A. M., El-Bannany, M., & Kanakkayil, S. (2023). A Powerful Predicting Model for Financial Statement Fraud Based on Optimized XGBoost Ensemble Learning Technique. *Applied Sciences*, *13*(4), 2272. https://doi.org/10.3390/app13042272

Ali, A., Abd Razak, S., Othman, S. H., Eisa, T. A. E., Al-Dhaqm, A., Nasser, M., Elhassan, T., Elshafie, H., & Saif, A. (2022). Financial Fraud Detection Based on Machine Learning: A Systematic Literature Review. *Applied Sciences*, *12*(19), 9637. https://doi.org/10.3390/app12199637

Arifin, A. L., & Koerniawan, K. A. (2025). Gender-diverse boards, liquidity, and financial distress: Pathways to fraud deterrence in auditor judgments. *Edelweiss Applied Science and Technology*, *9*(5), 2549–2564. https://doi.org/10.55214/25768484.v9i5.7517

Beneish, M. D. (1999). The Detection of Earnings Manipulation. *Financial Analysts Journal*, *55*(5), 24–36. https://doi.org/10.2469/faj.v55.n5.2296

Biegelman, M. T., & Bartow, J. T. (Eds.). (2012). *Executive Roadmap to Fraud Prevention and Internal Control: Creating a Culture of Compliance* (1st ed.). Wiley. https://doi.org/10.1002/9781119202356

Boulieris, P., Pavlopoulos, J., Xenos, A., & Vassalos, V. (2024). Fraud detection with natural language processing. *Machine Learning*, *113*(8), 5087–5108. https://doi.org/10.1007/s10994-023-06354-5

Chen, Y.-J., Wu, C.-H., Chen, Y.-M., Li, H.-Y., & Chen, H.-K. (2017). Enhancement of fraud detection for narratives in annual reports. *International Journal of Accounting Information Systems*, *26*, 32–45. https://doi.org/10.1016/j.accinf.2017.06.004

Cheung, A. B. L. (2013). Public governance reform in Hong Kong: Rebuilding trust and governability. *International Journal of Public Sector Management*, *26*(5), 421–436. https://doi.org/10.1108/IJPSM-05-2013-0070

Choi, D., & Lee, K. (2018). An Artificial Intelligence Approach to Financial Fraud Detection under IoT Environment: A Survey and Implementation. *Security and Communication Networks*, *2018*, 1–15. https://doi.org/10.1155/2018/5483472

Coetzee, P. (2016). Contribution of internal auditing to risk management: Perceptions of public sector senior management. *International Journal of Public Sector Management*, *29*(4), 348–364. https://doi.org/10.1108/IJPSM-12-2015-0215

Cressey, D. R. (1953). *Other People's Money: A Study in the Social Psychology of Embezzlement*. Free Press.

Dechow, P. M., Ge, W., Larson, C. R., & Sloan, R. G. (2011). Predicting Material Accounting Misstatements*: Predicting Material Accounting Misstatements. *Contemporary Accounting Research*, *28*(1), 17–82. https://doi.org/10.1111/j.1911-3846.2010.01041.x

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, *1*, 4171–4186.

Durtschi, C., Hillison, W., & Pacini, C. (2004). The effective use of Benford's Law to Assist in Detecting Fraud in Accounting Data. *Journal of Forensic Accounting*, *5*, 17–34.

FRC. (2022). *Professional Judgement Guidance*. The Financial Reporting Council. https://viewpoint.pwc.com/dt/uk/en/frc/frc_esma/other_frc_documents/assets/FRC_Professional_Judgement_Guidance_June_2022.pdf

Ghozali, I. (2023). *SEM dengan metode alternatif partial least squares [SEM with the alternative partial least squares method]* (5th ed). Badan Penerbit Universitas Diponegoro.

Gkegkas, M., Kydros, D., & Pazarskis, M. (2025). Using Data Analytics in Financial Statement Fraud Detection and Prevention: A Systematic Review of Methods, Challenges, and Future Directions. *Journal of Risk and Financial Management*, *18*(11), 598. https://doi.org/10.3390/jrfm18110598

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed). Sage.

Hammersley, J. S. (2011). A Review and Model of Auditor Judgments in Fraud-Related Planning Tasks. *AUDITING: A Journal of Practice & Theory*, *30*(4), 101–128. https://doi.org/10.2308/ajpt-10145

Hernandez Aros, L., Bustamante Molano, L. X., Gutierrez-Portela, F., Moreno Hernandez, J. J., & Rodríguez Barrero, M. S. (2024). Financial fraud detection through the application of machine learning techniques: A literature review. *Humanities and Social Sciences Communications*, *11*(1), 1130. https://doi.org/10.1057/s41599-024-03606-0

Hilal, W., Gadsden, S. A., & Yawney, J. (2022). Financial Fraud: A Review of Anomaly Detection Techniques and Recent Advances. *Expert Systems with Applications*, *193*, 116429. https://doi.org/10.1016/j.eswa.2021.116429

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied Logistic Regression* (1st ed.). Wiley. https://doi.org/10.1002/9781118548387

Humpherys, S. L., Moffitt, K. C., Burns, M. B., Burgoon, J. K., & Felix, W. F. (2011). Identification of fraudulent financial statements using linguistic credibility analysis. *Decision Support Systems*, *50*(3), 585–594. https://doi.org/10.1016/j.dss.2010.08.009

IAASB-ISA. (2019). *ISA 315 (Revised 2019): Identifying and Assessing the Risks of Material Misstatement*. IAASB, IFAC. https://www.iaasb.org/publications/isa-315-revised-2019-identifying-and-assessing-risks-material-misstatement

IAASB-ISA. (2025). *ISA 240 (Revised): The Auditor's Responsibilities Relating to Fraud in an Audit of Financial Statements*. IAASB, IFAC. https://www.iaasb.org/publications/isa-240-revised-auditor-s-responsibilities-relating-fraud-audit-financial-statements

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). *An Introduction to Statistical Learning: With Applications in R*. Springer US. https://doi.org/10.1007/978-1-0716-1418-1

Koerniawan, K. A. (2024). *Fraud Theories & Fraud Deterrence Propeller* (1st ed.). Tel-U Press, Telkom University. https://telupress.telkomuniversity.ac.id/product/fraud-theories-fraud-deterrence-propeller/

Koerniawan, K. A., Afiah, N. N., Sueb, M., & Suprijadi, J. (2022). Fraud Deterrence: The Management's Intention in Using FCP. *Quality - Access to Success*, *23*(190), 292–301. https://doi.org/10.47750/QAS/23.190.31

Koerniawan, K. A., Murti, G. T., Saraswati, R. S., & Hilda, H. (2024b). Assessing Fraud Deterrence In Private Health Clinics: Policy Implications From West Java. *Jurnal Reviu Akuntansi Dan Keuangan*, *14*(2), 350–379. https://doi.org/https://doi.org/10.22219/jrak.v14i2.32903

Koerniawan, K. A., Salim, D. F., Isynuwardhana, D., Pratomo, D., Murti, G. T., & Fidhien, F. G. (2025a). Integrating Fraud Deterrence Propeller and Continuous Auditing for Enhanced Fraud Detection and Sustainability. *ABAC Journal*, *45*(4). https://doi.org/10.59865/abacj.2025.38

Koerniawan, K. A., Triyanto, D. N., Wahyuni, D., & Farida, A. L. (2024c). Fraud Deterrence Propellers for Internal Control Quality Improvement. *Quality-Access to Success*, *25*(203). https://doi.org/10.47750/QAS/25.203.08

Mabel, S. N., Payamta, P., & Winarna, J. (2025). The development of fraud prevention policies in the public sector: A bibliometric analysis. *Jurnal Akuntansi & Auditing Indonesia*, 119–133. https://doi.org/10.20885/jaai.vol29.iss1.art10

Mautz, R. K., & Sharaf, H. A. (1961). *The Philosophy of Auditing*. American Accounting Association.

Nassif, A. B., Talib, M. A., Nasir, Q., & Dakalbab, F. M. (2021). Machine Learning for Anomaly Detection: A Systematic Review. *IEEE Access*, *9*, 78658–78700. https://doi.org/10.1109/ACCESS.2021.3083060

Nunnally, J. C. (1978). *Psychometric Theory* (2nd ed). McGraw-Hill.

Pourhabibi, T., Ong, K.-L., Kam, B. H., & Boo, Y. L. (2020). Fraud detection: A systematic literature review of graph-based anomaly detection approaches. *Decision Support Systems*, *133*, 113303. https://doi.org/10.1016/j.dss.2020.113303

Singleton, T. W., Singleton, A. J., Bologna, G. J., & Lindquist, R. J. (2016). *Fraud auditing and forensic accounting* (3rd ed). John Wiley & Sons.

SPAP SA 240 Rev 2021. (2021). *SA 240 (Revisi 2021)—Tanggung Jawab Auditor Terkait Dengan Kecurangan Dalam Suatu Audit Atas Laporan Keuangan (Auditor's Responsibilities Regarding Fraud in an Audit of Financial Statements)*. Dewan Standar SPAP, IAPI.

SPAP SA 315 Rev 2021. (2021). *SA 315 (Revisi 2021)—Pengidentifikasian Dan Penilaian Risiko Kesalahan Penyajian Material (Identifying and Assessing the Risk of Material Misstatement)*. Dewan Standar SPAP, IAPI.