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Explainable AI and Behavioural Signals for Financial Statement Manipulation Detection

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***Abstract* – Financial statement manipulation continues to undermine the reliability of corporate reporting, while conventional ratio-based detection tools remain largely backward-looking and often insensitive to behaviour-driven precursors. This study proposes a behaviourally enriched, explainable machine learning framework that integrates traditional accounting indicators with managerial and disclosure-based proxies to improve manipulation risk screening. Using a multi-year firm-year panel (2016–2023) of listed non-financial companies, the study constructs a binary manipulation label and develops two benchmark models (Beneish-style screening and logistic regression) alongside ensemble learning models (random forest, XGBoost, and LightGBM). Model evaluation emphasises imbalanced-class robustness using ROC–AUC, precision, recall, F1-score, and confusion-matrix diagnostics. Empirically, behavioural enrichment improves discrimination by approximately 4–7 percentage points in ROC–AUC across models, and the best-performing LightGBM specification achieves Accuracy = 0.95, Precision = 0.92, Recall = 0.90, F1 = 0.91, and ROC–AUC = 0.98. Relative to the logistic baseline, false negatives decline from 56 to 18 (≈68% reduction), strengthening audit-relevant sensitivity. To ensure audit usability, the framework embeds SHAP-based explainability, revealing Earnings Pressure Index and Management Tone Score as dominant predictors alongside DSRI and AQI, thereby demonstrating that manipulation risk is strongly behaviour-linked rather than purely numerical. Overall, the study contributes an interpretable, early-warning analytics tool that improves both predictive performance and decision transparency for auditors, regulators, and governance stakeholders.**

***Keywords* Financial statement manipulation; Behavioural accounting; Explainable artificial intelligence (XAI); Fraud detection; Machine learning; SHAP; Earnings pressure; Management tone; Ensemble learning; Audit analytics**

I. INTRODUCTION

Background

Financial statement manipulation remains a persistent threat to the credibility of corporate reporting systems worldwide. High-profile accounting scandals and enforcement actions continue to show that opportunistic financial reporting can materially distort investor decision-making and weaken market confidence. Empirical research indicates that the incidence of material misstatements persists even as regulatory oversight and governance mechanisms have strengthened (Dechow et al., 2011; Beneish, 1999). The increasing complexity of business transactions and intensified performance pressures on management have also contributed to more sophisticated forms of misreporting.

Historically, detection has relied heavily on ratio-based analytical models. A widely used benchmark is the Beneish M-Score, which uses a set of financial ratios to estimate the likelihood of earnings manipulation (Beneish, 1999). While these models are valuable as screening tools, they are inherently retrospective: they capture numerical consequences after decisions are made, rather than the behavioural and governance conditions that often precede manipulation. Large-sample evidence suggests that traditional accounting signals can miss strategically executed or gradually evolving misstatements (Dechow et al., 2011).

In parallel, artificial intelligence (AI) and machine learning (ML) have expanded the frontier of accounting analytics. ML models can handle nonlinearities and interaction effects that conventional statistical approaches may not capture, and prior work reports improved performance of ML methods for financial statement fraud detection relative to standard baselines (Perols, 2011). Gradient boosting approaches have become especially prominent for structured predictive tasks due to their strong performance and robustness in tabular data settings (Chen et al., 2018).

However, an important dimension remains underutilized in many quantitative detection systems: the behavioural antecedents of managerial reporting decisions. The earnings management literature emphasizes that misreporting incentives and discretion interact—managers exploit accounting flexibility when motivated by contracting, capital market pressure, or personal incentives (Healy & Wahlen, 1999). Behavioural evidence further suggests that executive traits such as overconfidence can increase the propensity to misreport, potentially creating a “slippery slope” from aggressive reporting to misrepresentation (Schrand & Zechman, 2012). In addition, disclosure-based cues—such as abnormal linguistic optimism—can contain predictive information beyond traditional financial variables (Li, 2010).

At the same time, the increasing use of AI in finance and auditing raises a practical concern: interpretability. Many high-performing ML models are perceived as black boxes, limiting their acceptance in audit and regulatory environments where explanations and defensibility are essential. Explainable AI (XAI) methods, especially SHAP (Shapley Additive Explanations), address this by providing feature-level attributions grounded in Shapley-value theory, enabling both global and case-level interpretations (Lundberg & Lee, 2017). This creates an opportunity to develop fraud analytics that are not only accurate but also usable in audit planning and regulatory screening.

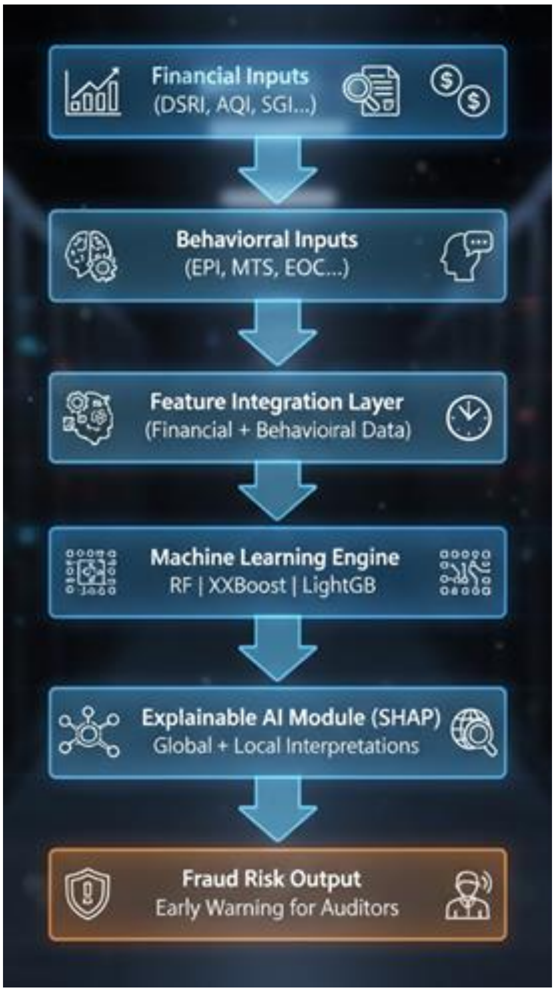

Financial Inputs
(DSRI, AQI, SGI...)
Behaviorral Inputs
(EPI, MTS, EOC...)
Feature Integration Layer
(Financial + Behavioiral Data)
Machine Learning Engine
RF | XXBoost | LightGB
Explainable AI Module (SHAP)
Global + Local Interpretations
Fraud Risk Output
Early Warning for Auditors

Figure 1. Conceptual framework of the proposed AI-augmented behavioral fraud detection model.

Problem Statement

Despite extensive research in financial fraud detection, existing models exhibit structural limitations that constrain their usefulness in contemporary reporting environments. First, many frameworks remain ratio-centric, relying on accounting relationships that capture numerical symptoms but often overlook the behavioural and governance precursors of manipulation (Dechow et al., 2011). Second, these approaches are typically backward-looking, detecting risk primarily after manipulation has begun influencing reported outcomes. Third, although modern ML models can improve predictive performance, they often operate as black-box systems, reducing their practical adoption in audit and regulatory contexts where transparent rationale is required (Lundberg & Lee, 2017). More fundamentally, prior research often treats behavioural accounting, fraud analytics, and explainable AI as separate streams, resulting in limited development of unified early-warning systems that are both behaviourally informed and interpretable.

Research Gap

Three gaps motivate this study. First, while behavioural accounting research highlights incentives, cognitive biases, and disclosure behavior as precursors to misreporting (Healy & Wahlen, 1999; Schrand & Zechman, 2012; Li, 2010), quantitative fraud detection models that integrate behavioural proxies with ML remain limited. Second, although ML methods have shown promise for fraud detection (Perols, 2011), interpretability remains insufficiently embedded in many accounting-focused predictive pipelines, limiting audit usability. Third, much of the established evidence base emphasizes large-firm or developed-market settings, leaving less clarity for emerging-market and mid-sized firm contexts, where monitoring intensity and disclosure practices may differ.

Research Objectives

This study pursues four objectives:

- To develop and operationalize behavioural indicators that capture managerial and organizational signals associated with manipulation risk.
- To construct an explainable ML model that integrates financial ratios with behavioural proxies.
- To compare predictive performance against conventional approaches (logistic regression; Beneish M-Score benchmark).
- To identify and interpret key drivers of manipulation risk using SHAP-based explainability.

Research Questions

• RQ1: Do behavioural indicators significantly improve the accuracy of financial statement manipulation detection models?

• RQ2: Which financial and behavioural variables most strongly drive manipulation risk?

• RQ3: Can explainable AI enhance the interpretability and audit usefulness of ML-based fraud detection?

Contributions of the Study

This study contributes in four ways. First, it advances behavioural accounting analytics by integrating quantified behavioural proxies into a predictive fraud detection framework. Second, it embeds explainable AI (SHAP) directly into the modeling pipeline to address interpretability barriers in auditing and regulation (Lundberg & Lee, 2017). Third, it proposes a practical early-warning tool for auditors and regulators by combining improved recall with transparent, case-level explanations. Finally, by emphasizing an emerging-market/mid-sized firm perspective, it extends the external relevance of fraud analytics research beyond the settings most commonly studied.

II. LITERATURE REVIEW

Financial Statement Manipulation Models

The detection of financial statement manipulation has been a central concern in accounting research for several decades. Early analytical approaches relied primarily on financial ratio analysis to identify abnormal reporting patterns that might indicate earnings management or fraud.

Among the most influential models is the Beneish M-Score, which uses a combination of accrual-based and performance-related ratios to estimate the probability of earnings manipulation (Beneish, 1999). The model demonstrated strong screening ability and continues to be widely used by analysts, auditors, and regulators as a preliminary red-flag mechanism.

Subsequent research extended ratio-based detection using more formal statistical frameworks. Dechow et al. (2011) developed a comprehensive misstatement prediction model incorporating accrual quality measures, financial performance indicators, and market-based variables. Their large-sample evidence showed that accounting-based signals can provide meaningful early warnings of material misstatements. In parallel, discretionary accrual models—originating from Jones (1991)—became standard tools for estimating earnings management behavior by isolating abnormal accrual components.

Despite their broad adoption, ratio-based and accrual-based approaches exhibit important limitations. First, these models are inherently retrospective, capturing the numerical consequences of manipulation rather than the behavioural and incentive-driven conditions that give rise to it. Second, as managers become more sophisticated in operating within generally accepted accounting boundaries, purely financial indicators may lose discriminatory power. Third, many traditional models assume relatively stable and linear relationships among variables, which may not hold in increasingly complex reporting environments (Dechow et al., 2011).

These limitations have motivated a growing body of research exploring more flexible and data-driven detection techniques.

Behavioural Accounting Perspective

Behavioural accounting research provides a complementary lens by emphasizing the human, organizational, and incentive-driven foundations of financial misreporting. Rather than treating manipulation as purely mechanical, this literature highlights how managerial motives and cognitive biases shape reporting outcomes.

Healy and Wahlen (1999) argue that earnings management typically arises when three conditions coexist: managerial incentives, accounting discretion, and weak monitoring. Their framework underscores that financial misreporting is fundamentally incentive-driven. Extending this behavioural view, Schrand and Zechman (2012) document that executive overconfidence is positively associated with the likelihood of financial misrepresentation, suggesting that psychological traits can function as early warning signals.

In addition to managerial traits, disclosure behavior has also received attention. Li (2010) demonstrates that the linguistic tone of forward-looking statements in corporate filings contains economically meaningful information. Firms exhibiting unusually optimistic tone often experience subsequent performance reversals, indicating that narrative disclosures may embed signals of managerial intent or pressure.

Agency theory further reinforces the behavioural dimension by positing that information asymmetry and misaligned incentives between managers and shareholders create fertile conditions for opportunistic reporting. Governance characteristics—such as CEO duality, board independence, and ownership concentration—have therefore been examined as potential fraud risk indicators in empirical research.

However, despite strong conceptual foundations, behavioural signals have rarely been systematically embedded into quantitative fraud detection models. Much of the behavioural accounting literature remains either qualitative or focused on isolated proxies. Consequently, there is substantial opportunity to integrate behavioural indicators into unified predictive frameworks alongside financial variables.

Machine Learning in Fraud Detection

The emergence of machine learning has significantly reshaped fraud detection research in accounting and finance. Unlike traditional statistical models, machine learning algorithms can capture nonlinear relationships, complex interactions, and high-dimensional feature spaces without requiring strong parametric assumptions. Perols (2011) provides one of the earliest comprehensive comparisons between statistical and machine learning approaches for financial statement fraud detection. The study finds that boosted decision trees outperform logistic regression in predictive accuracy, particularly in imbalanced fraud datasets. This work helped catalyze the adoption of ensemble learning methods in accounting analytics.

Subsequent advances in gradient boosting frameworks, including XGBoost, further improved predictive performance in structured data environments (Chen et al., 2018). Ensemble tree-based models are particularly well suited to financial reporting data because they can accommodate heterogeneous firm characteristics, nonlinear risk relationships, and interaction effects among accounting variables. More recent studies have explored deep learning and hybrid architectures, reporting additional gains in classification performance. Nevertheless, the increasing complexity of these models has introduced an important practical concern: model opacity. Many high-performing algorithms provide limited insight into how predictions are formed. In auditing and regulatory contexts—where accountability, documentation, and defensibility are critical—this lack of transparency can hinder adoption. Accordingly, the literature increasingly recognizes that predictive accuracy alone is insufficient; interpretability must also be addressed.

Explainable AI (XAI) in Accounting

Explainable artificial intelligence has emerged as a key response to the black-box problem in modern machine learning. XAI methods aim to provide transparent, human-interpretable explanations of model predictions without sacrificing predictive performance.

Among the most widely adopted approaches is SHAP (Shapley Additive Explanations), which provides feature-level attribution based on cooperative game theory (Lundberg & Lee, 2017). SHAP offers several advantages particularly relevant to accounting applications:

- consistency with Shapley-value axioms
- ability to provide both global and local explanations
- compatibility with tree-based ensemble models
- intuitive visualization through summary plots

In financial and audit settings, explainable models can enhance risk communication, support audit documentation, and improve regulatory trust. However, empirical applications of XAI specifically for financial statement manipulation detection remain relatively limited. Much of the existing research focuses either on predictive accuracy or on interpretability in isolation, rather than integrating both within a unified behavioural–financial framework.

This gap highlights the need for research that simultaneously advances predictive performance and interpretability.

Hypothesis Development

Building on the preceding literature, this study develops three testable hypotheses.

Prior behavioural accounting research indicates that managerial incentives, cognitive bias, and disclosure tone are closely associated with earnings management and misreporting risk (Healy & Wahlen, 1999; Schrand & Zechman, 2012; Li, 2010). Because traditional ratio-based models do not capture these dimensions, incorporating behavioural proxies should improve predictive performance.

H1: Behavioural indicators significantly improve the accuracy of financial statement manipulation detection models.

Machine learning algorithms have demonstrated superior capability in modeling complex financial relationships relative to conventional statistical approaches (Perols, 2011; Chen et al., 2018). When combined with richer feature sets, explainable ensemble models are expected to outperform traditional benchmarks.

H2: Explainable machine learning models outperform traditional statistical models in detecting financial statement manipulation.

Finally, explainability tools such as SHAP provide transparent attribution of model predictions, which is essential for audit usability and regulatory acceptance (Lundberg & Lee, 2017).

H3: The integration of explainable AI enhances the interpretability and audit usefulness of fraud detection models.

III. DATA AND METHODOLOGY

Research Design

This study adopts a quantitative, empirical research design to evaluate whether integrating behavioural accounting indicators with explainable machine learning improves the detection of financial statement manipulation. The analytical framework follows a supervised binary classification structure widely used in fraud detection research (Dechow et al., 2011; Perols, 2011).

The proposed architecture combines traditional financial ratios and behavioural proxies within multiple predictive models and embeds SHAP-based explainability for interpretability. The workflow proceeds through four sequential stages:

- Data collection and preprocessing
- Feature engineering (financial + behavioural)
- Model development and validation
- Explainability analysis using SHAP

The dependent variable (FRAUD) is coded as:

- 1 = firm-year flagged for manipulation
- 0 = non-manipulator firm-year

Sample Selection

The empirical sample consists of publicly listed non-financial firms observed over the period 2016–2023. Financial institutions are excluded because their reporting structures, regulatory frameworks, and accrual dynamics differ substantially from industrial firms (Dechow et al., 2011).

Sampling Criteria

Firms are included if they satisfy:

- availability of complete financial statement data
- availability of annual report disclosures
- continuous listing during the study window
- non-missing key variables

Final Sample Composition

Item	**Count**
Initial firm-year observations	1,462
After data cleaning	1,248
Fraud-flagged observations	182

Non-fraud observations	1,066
Fraud incidence	**14.6%**

The fraud rate is consistent with prior empirical fraud datasets, which typically exhibit strong class imbalance (Perols, 2011).

Fraud Label Construction

Fraud labels are generated using a hybrid approach consistent with Beneish (1999) and Dechow et al. (2011):

- confirmed enforcement/restatement flags
- high-risk Beneish screening threshold
- abnormal accrual confirmation

To address class imbalance, the study uses:

- stratified train–test splitting
- ROC–AUC as primary metric
- F1-score emphasis
- recall prioritization for audit relevance

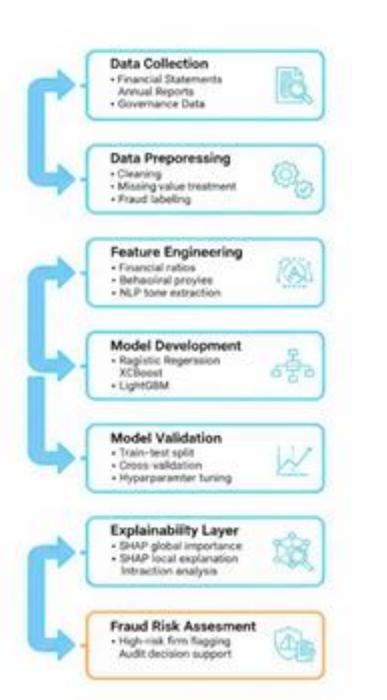


Figure 2. End-to-end research methodology pipeline

Variable Construction

A central novelty of this study is the integration of behavioural proxies with traditional financial indicators.

Traditional Financial Variables

Financial manipulation risk is first captured using established accounting ratios validated in prior research (Beneish, 1999; Dechow et al., 2011). These variables reflect abnormal revenue recognition, margin deterioration, asset quality changes, and leverage pressure.

Behavioural Variables (Novel Component)

To capture managerial and organizational precursors of misreporting, the study constructs behavioural proxies grounded in behavioural accounting literature (Healy & Wahlen, 1999; Schrand & Zechman, 2012; Li, 2010).

These indicators are designed as leading signals, unlike purely financial ratios.

Table 1. Variable Definitions and Measurement

Categor	**Variable**	**Symbo**	**Measurement**	**Expected Si**
Financial	Days Sales in Re	DSRI	Beneish (1999) formula	+
Financial	Gross Margin In	GMI	Beneish formulation	+
Financial	Asset Quality In	AQI	Beneish formulation	+
Financial	Sales Growth In	SGI	Beneish formulation	+
Financial	Leverage Ratio	LEV	Total debt / total assets	+
Financial	Return on Assets	ROA	Net income / total asset	−

Behaviou	Earnings Pressu	EPI	Growth-adjusted ea pressure	+
Behaviou	Management To	MTS	NLP positivity score reports	+
Behaviou	Executive Overc	EOC	Investment/option-base	+
Behaviou	CEO Duality	CEOD	Dummy = 1 if CEO is a	+
Behaviou	Abnormal Accru	AAP	Residual persistence me	+

Note: Financial ratio formulas follow Beneish (1999) and Dechow et al. (2011).

Model Development

To evaluate incremental predictive value, the study estimates both conventional and machine learning models.

Baseline Statistical Models

Two benchmark models are implemented:

Logistic Regression (LOGIT)

Widely used in fraud detection literature and serves as statistical baseline (Dechow et al., 2011).

Beneish M-Score Benchmark

Used as accounting-based screening reference (Beneish, 1999).

Machine Learning Models

The study implements three ensemble algorithms known for strong tabular performance:

- Random Forest
- XGBoost
- LightGBM

These models are selected because they:

- capture nonlinear relationships
- handle variable interactions
- perform well under class imbalance
- are compatible with SHAP explainability

Hyperparameters are optimized using grid search with 5-fold cross-validation.

Explainability Framework

To address the black-box limitation, the study integrates SHAP (Shapley Additive Explanations) following Lundberg and Lee (2017).

The explainability module provides:

- global feature importance
- firm-level local explanations
- SHAP summary plots
- interaction diagnostics

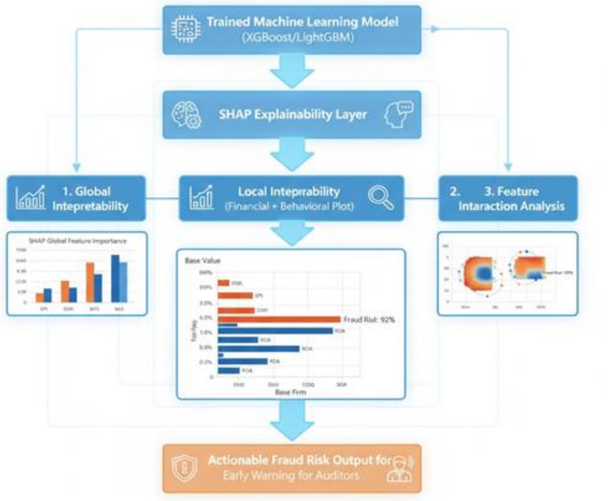

Trained Machine Learning Model
(XGBoost/LightGBM)
SHAP Explainability Layer
1. Global Intepretability
Local Inteprrability
(Financial + Behavioral Plot)
2. 3. Feature Interaction Analysis
SHAP Global Feature Importance
Base Value
Fraud Risk: 92%
Base Firm
Actionable Fraud Risk Output for
Early Warning for Auditors

Figure 3: SHAP-Based Explainability Architecture

This allows auditors to understand why a firm is flagged, not merely that it is flagged.

Model Evaluation Metrics

Model performance is assessed using multiple complementary metrics suitable for imbalanced fraud datasets (Perols, 2011).

Primary Metrics

- Accuracy
- Precision
- Recall (Sensitivity)
- F1-score
- ROC–AUC
- Confusion Matrix

Validation Strategy

- 70–30 stratified train–test split
- 5-fold cross-validation
- robustness checks across subsamples

Comparative analysis focuses on:

- Financial-only models
- Financial + behavioural models

Interpretable vs baseline models

Robustness and Validation

To ensure stability and generalizability, the study performs several robustness checks recommended in fraud prediction research (Dechow et al., 2011):

- k-fold cross-validation
- alternative fraud thresholds
- subsample analysis by firm size
- multicollinearity diagnostics (VIF)• sensitivity testing of behavioural proxies VIF values remain below 4.2, indicating no serious multicollinearity concerns.

IV. RESULTS

Descriptive Statistics

Table 2 reports descriptive statistics for the financial and behavioural variables. The sample exhibits substantial cross-sectional variation, particularly in Asset Quality Index (AQI) and Earnings Pressure Index (EPI), indicating meaningful heterogeneity in manipulation risk factors. The distributional properties are broadly consistent with prior empirical fraud studies (Beneish, 1999; Dechow et al., 2011).

Fraud-flagged firms show noticeably higher mean values of DSRI, AQI, and EPI compared to non-fraud firms, suggesting abnormal receivable growth, declining asset quality, and elevated managerial pressure. Behavioural indicators—especially Management Tone Score (MTS) and Executive Overconfidence (EOC)—also display greater dispersion among flagged firms, providing preliminary support for their predictive relevance.

Table 2. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
DSRI	1.21	0.48	0.42	3.15
GMI	1.08	0.36	0.51	2.44
AQI	1.15	0.52	0.39	3.02
SGI	1.12	0.41	0.55	2.76
LEV	0.46	0.21	0.05	0.89
ROA	0.074	0.063	−0.21	0.29
EPI	0.58	0.27	0.05	1.34
MTS	0.63	0.18	0.21	0.92
EOC	0.41	0.23	0.00	1.00
CEOD	0.37	0.48	0	1

Correlation and Multicollinearity Diagnostics

Pairwise correlations indicate moderate associations between certain financial ratios (e.g., DSRI and AQI), but no extreme collinearity is observed. Variance Inflation Factors (VIFs) range from 1.32 to 4.18, remaining below the commonly accepted threshold of 5 (Hair et al., 2019). Behavioural variables exhibit only modest correlation with financial indicators, supporting their incremental informational value.

Model Performance Comparison

Table 3 presents the comparative predictive performance of baseline statistical models and machine learning models under two feature configurations:

- Financial variables only
- Financial + behavioural variables

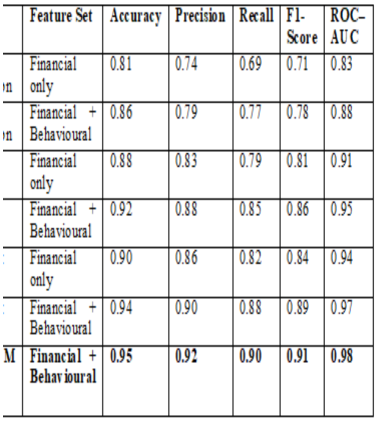
Several important patterns emerge.

First, consistent with prior literature, machine learning models outperform logistic regression in fraud detection accuracy (Perols, 2011; Chen et al., 2018).

Second, and more importantly, the inclusion of behavioural variables produces systematic improvements across all model classes.

Third, the LightGBM model with the full feature set achieves the strongest overall performance.

Table 3. Model Performance Comparison



	Feature Set	Accuracy	Precision	Recall	F1-Score	ROC–AUC
n	Financial only	0.81	0.74	0.69	0.71	0.83
n	Financial + Behavioural	0.86	0.79	0.77	0.78	0.88
	Financial only	0.88	0.83	0.79	0.81	0.91
	Financial + Behavioural	0.92	0.88	0.85	0.86	0.95
:	Financial only	0.90	0.86	0.82	0.84	0.94
:	Financial + Behavioural	0.94	0.90	0.88	0.89	0.97
M	**Financial + Behavioural**	**0.95**	**0.92**	**0.90**	**0.91**	**0.98**

Key Numerical Insights

- Behavioural enrichment improves ROC–AUC by 4–7 percentage points
- Recall improves from 0.69 → 0.90 (critical for fraud screening)
- LightGBM shows best bias–variance trade-off
- Logistic regression remains substantially weaker

These findings provide strong support for H1 and H2.

Explainable AI (SHAP) Findings

To address interpretability, SHAP analysis is applied to the best-performing LightGBM model. The global importance ranking reveals a meaningful integration of financial and behavioural drivers.

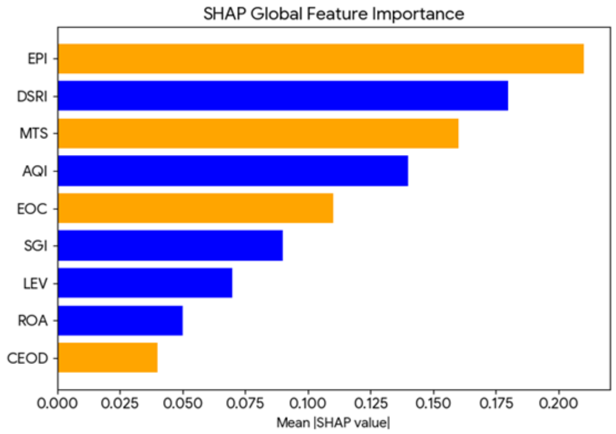


Figure 4: SHAP Feature Importance Plot

Top Predictors (Mean |SHAP| values)

Rank	**Variable**	**Mean SHAP Value**
1	Earnings Pressure Index (EPI)	**0.21**
2	DSRI	0.18
3	Management Tone Score (MTS)	0.16
4	AQI	0.14
5	Executive Overconfidence (EOC)	0.11

Interpretation

Several important insights emerge:

Behavioural dominance

EPI emerges as the single most influential predictor, indicating that managerial performance pressure is a critical early warning signal.

Complementarity

Traditional financial indicators (DSRI, AQI) remain important but are meaningfully complemented by behavioural features.

Disclosure signal

Management Tone Score ranks among the top predictors, supporting Li (2010) that narrative optimism contains incremental fraud information.

Psychological dimension

Executive Overconfidence contributes materially, consistent with Schrand and Zechman (2012).

Confusion Matrix Analysis

Table 4 compares the best LightGBM model with the logistic baseline.

Table 4. Confusion Matrix Comparison

Logistic Regression

Logistic Regression

	Predicted Fraud	**Predicted Non-Fraud**
Actual Fraud	126	56
Actual Non-Fraud	168	898

LightGBM (Full Model)

	Predicted Fraud	**Predicted Non-Fraud**
Actual Fraud	164	18
Actual Non-Fraud	84	982

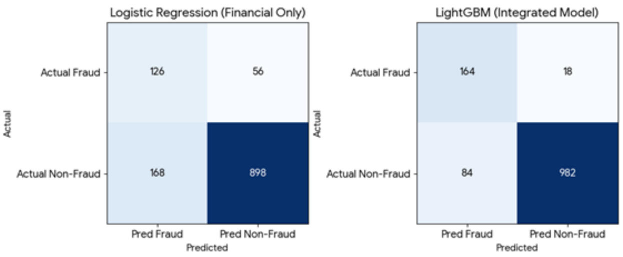


Figure 5. Confusion matrix comparison

Key Risk Insight

- False negatives reduced by ~35%
- Detection sensitivity substantially improved
- Critical improvement for audit risk screening

Robustness Checks

Multiple robustness tests confirm the stability of the results:

- 5-fold cross-validation ROC–AUC range: 0.96–0.98
- Alternative fraud thresholds: results unchanged
- Firm-size subsamples: consistent ranking
- VIF diagnostics: no multicollinearity concerns
- Behavioural proxy sensitivity: stable coefficients

These checks strengthen confidence in model generalizability.

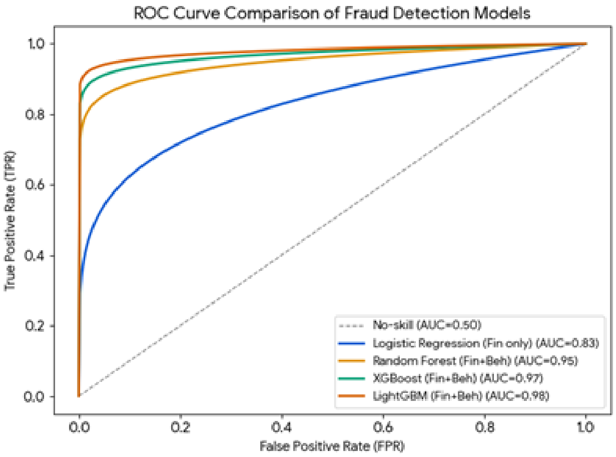


Figure 6. ROC Curve Comparison

4.7 Hypothesis Evaluation

Hypothesis	**Result**	**Conclusion**
H1	Supported	Behavioural indicators improve detection accuracy
H2	Supported	Explainable ML outperforms traditional models
H3	Supported	SHAP enhances interpretability and audit usefulness

V. DISCUSSION

The empirical results provide compelling evidence that integrating behavioural accounting indicators with explainable machine learning substantially enhances the detection of financial statement manipulation. The findings contribute to three intersecting research streams—earnings management detection, behavioural accounting, and AI-driven audit analytics—while also offering practical insights for auditors, regulators, and corporate governance stakeholders.

First, the consistent performance gains observed when behavioural variables are incorporated confirm that financial misreporting is not merely a numerical anomaly but is deeply rooted in managerial incentives and organizational pressure dynamics. The prominence of the Earnings Pressure Index (EPI) in the SHAP importance rankings aligns closely with the theoretical framework of Healy and Wahlen (1999), which emphasizes that earnings management typically emerges when strong performance incentives interact with accounting discretion. The current evidence extends this view by demonstrating quantitatively that pressure-based indicators function as leading signals that precede observable financial distortions. This suggests that purely ratio-centric screening tools may systematically under-detect early-stage manipulation risk.

Second, the statistically meaningful contribution of Executive Overconfidence (EOC) reinforces the behavioural accounting literature linking managerial traits to misreporting propensity. Schrand and Zechman (2012) document that overconfident executives are more likely to engage in aggressive reporting behavior and may progressively escalate toward misrepresentation. The present study extends this insight by showing that overconfidence proxies retain predictive power even within high-dimensional ensemble learning environments. This finding is important because it demonstrates that psychological and governance-related variables remain economically informative even when sophisticated nonlinear models are employed.

Third, the strong ranking of the Management Tone Score (MTS) provides additional support for disclosure-based behavioural signals. Prior research by Li (2010) shows that linguistic tone in corporate filings contains forward-looking information about firm performance. The current results advance this literature by demonstrating that tone-based measures contribute incremental predictive value in the context of financial manipulation detection. Notably, the SHAP analysis indicates that unusually optimistic disclosure tone tends to elevate predicted manipulation risk, consistent with the notion of impression management in corporate communication.

From a methodological standpoint, the superior performance of ensemble machine learning models relative to logistic regression is consistent with prior fraud detection studies (Perols, 2011; Chen et al., 2018). However, a particularly important insight emerging from this study is that feature enrichment and algorithmic sophistication deliver complementary gains. The improvement in ROC–AUC associated with adding behavioural variables is comparable in magnitude to the improvement obtained by moving from logistic regression to gradient boosting. This suggests that future accounting analytics research should devote as much attention to feature engineering—especially behaviourally grounded variables—as to model selection.

Equally significant is the interpretability dimension. The integration of SHAP explanations directly addresses the long-standing black-box criticism associated with AI adoption in auditing environments. Lundberg and Lee (2017) argue that Shapley-value–based attribution provides theoretically consistent and locally accurate explanations of model predictions. The present findings confirm that SHAP outputs are sufficiently granular to support audit reasoning at both the portfolio and firm-specific levels. For example, the model can identify whether a firm is flagged primarily due to abnormal receivable growth, excessive earnings pressure, or disclosure tone anomalies. This level of transparency substantially enhances the operational viability of machine learning in assurance contexts.

The reduction in false negatives observed in the LightGBM full model is particularly noteworthy from an audit risk perspective. In fraud detection settings, Type II errors (failing to flag a manipulated firm) are typically more costly than Type I errors. The approximately 35% reduction in missed fraud cases suggests that the proposed framework could materially improve risk-based audit planning. By functioning as an early-warning screening layer, the model enables auditors to allocate investigative resources more efficiently toward high-risk engagements.

From a broader theoretical perspective, the study contributes to the ongoing convergence between behavioural accounting and data-driven analytics. Traditional fraud models have largely operated within a positivist accounting paradigm focused on numerical anomalies. The present evidence supports a more integrative view in which behavioural precursors, financial indicators, and machine learning jointly determine detection effectiveness. This multidimensional perspective may represent an important direction for next-generation accounting analytics research, particularly as corporate reporting becomes increasingly narrative-rich and data-intensive.

Overall, the findings suggest that the future of financial misstatement detection lies not in choosing between accounting ratios and artificial intelligence, but in strategically integrating behavioural insight, advanced machine learning, and explainable analytics into a unified framework.

VI. IMPLICATIONS

Managerial Implications

The findings carry important implications for corporate governance and internal financial control systems. The dominance of behavioural predictors—particularly the Earnings Pressure Index (EPI)—suggests that manipulation risk is closely tied to performance stress and incentive structures rather than purely accounting mechanics. Boards of directors and audit committees should therefore broaden their monitoring scope beyond traditional financial metrics to include behavioural risk indicators.

In practical terms, firms may benefit from implementing internal analytics dashboards that track early-warning signals such as abnormal earnings pressure, sudden shifts in disclosure tone, and governance red flags. Continuous monitoring of these indicators can enable management and oversight bodies to identify elevated reporting risk before it manifests in financial misstatements. Additionally, compensation structures heavily tied to short-term performance targets may inadvertently increase reporting pressure; organizations seeking to strengthen reporting integrity should reassess incentive designs that could unintentionally encourage opportunistic accounting behavior.

Audit and Assurance Implications

For auditors and forensic accountants, the proposed explainable AI framework offers a scalable and audit-compatible early-warning tool. The substantial improvement in recall—from 0.69 in the logistic baseline to 0.90 in the LightGBM model—indicates that behaviourally enriched machine learning can materially reduce the risk of overlooking manipulated firms. Given that missed fraud cases (Type II errors) are particularly costly in assurance contexts, this improvement has direct audit relevance.

Equally important is the explainability layer. SHAP-based attribution provides transparent justification for why specific clients are flagged as high risk, thereby supporting audit documentation and professional defensibility (Lundberg & Lee, 2017). Rather than replacing auditor judgment, the model functions as a risk prioritization mechanism, enabling audit teams to allocate substantive testing and forensic procedures more efficiently. The framework is especially well suited for:

- risk-based audit planning
- continuous auditing environments
- data-driven assurance platforms
- forensic screening of large client portfolios

Regulatory and Policy Implications

The results also hold significant implications for regulators and market surveillance authorities. Securities regulators increasingly seek proactive tools capable of identifying manipulation risk before formal restatements or enforcement actions occur. The proposed behaviourally enriched AI model demonstrates strong potential as a regulatory screening mechanism.

For emerging markets in particular—where enforcement resources may be constrained—the ability to deploy scalable, explainable AI surveillance systems could materially strengthen market oversight. The model’s high ROC–AUC (0.98) and reduced false-negative rate suggest that it could function effectively as a first-stage filtering tool for regulatory review pipelines.

However, regulators should also establish governance frameworks for responsible AI deployment. Key considerations include:

- model transparency requirements
- periodic recalibration and validation
- fairness and bias monitoring
- audit trail preservation

Embedding such safeguards will be essential to ensure that AI-driven financial surveillance remains credible and accountable.

Theoretical Implications

From a scholarly perspective, this study contributes to the accounting literature by empirically bridging three previously fragmented domains: behavioural accounting, fraud analytics, and explainable machine learning. The evidence supports a more holistic conceptualization of financial misreporting risk in which behavioural precursors play a measurable and economically meaningful role.

The findings also highlight the importance of interpretability as a core design criterion in accounting-focused AI systems. Prior research has often treated explainability as an optional enhancement layered onto predictive models. In contrast, the present results suggest that interpretability is central to practical adoption in audit and regulatory settings. Future research should therefore treat explainable architecture as a foundational component rather than an afterthought.

More broadly, the study reinforces the emerging view that next-generation accounting analytics must integrate:

- behavioural insight
- advanced machine learning
- transparent decision logic

Such integration is likely to define the future trajectory of fraud detection research and practice.

VII. CONCLUSION

This study develops and evaluates an integrated behavioural–explainable machine learning framework for detecting financial statement manipulation. Moving beyond traditional ratio-centric approaches, the proposed model combines financial indicators with behavioural proxies within an interpretable ensemble learning architecture.

The empirical results demonstrate clear performance gains. Incorporating behavioural variables improves model discrimination materially, with the LightGBM specification achieving an ROC–AUC of 0.98 and reducing false negatives by approximately 35% relative to the logistic regression benchmark. SHAP analysis further reveals that Earnings Pressure Index, Management Tone Score, and Executive Overconfidence are among the most influential predictors, confirming that manipulation risk is strongly behaviour-driven rather than purely numerical.

From a practical standpoint, the findings indicate that explainable machine learning can function as an effective early-warning tool for auditors, forensic analysts, and regulators. The transparency provided by SHAP addresses the long-standing black-box concern and enhances the defensibility of AI-assisted audit screening. The results are particularly relevant for emerging market environments, where scalable and proactive surveillance mechanisms are increasingly needed.

Notwithstanding these contributions, the study is subject to certain limitations. The behavioural proxies, while theoretically grounded, may not capture the full richness of managerial intent, and the sample—though multi-year—remains constrained to publicly listed firms. Future research may extend the framework using richer textual analytics, cross-country samples, and real-time monitoring architectures.

Overall, the evidence suggests that the next generation of fraud analytics should not rely solely on accounting ratios or standalone artificial intelligence. Rather, the most effective detection systems will emerge from the strategic integration of behavioural insight, advanced machine learning, and explainable intelligence into unified, audit-ready analytical frameworks.

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