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Application of Artificial Intelligence in Detecting Creative Accounting Tendencies Among Corporations in Kenya

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Abstract

The rapid advancement of Artificial Intelligence (AI) has transformed auditing and financial reporting, offering novel approaches to detecting creative accounting practices. This study investigates the effectiveness of AI in identifying financial irregularities among selected Kenyan corporations, comparing AI-driven techniques with traditional accrual-based models, including the Modified Jones Model and the Beneish M-Score. Using a mixed-methods design, secondary financial data spanning five years from four road transport companies were analyzed alongside qualitative insights from finance managers and internal auditors. AI techniques, including anomaly detection models and explainable AI tools, effectively identified complex, multi-dimensional patterns indicative of earnings manipulation, corroborating findings from traditional models in severe cases. The results demonstrate that AI complements classical detection methods by capturing non-linear relationships and emergent manipulative practices that conventional models may overlook. The study further highlights the importance of organizational readiness, auditor training, and regulatory frameworks to ensure the ethical and effective deployment of AI in financial reporting. Findings suggest that integrating AI into auditing practices can enhance accuracy, efficiency, and transparency, thereby strengthening corporate governance and stakeholder trust.

Keywords: Artificial Intelligence, Creative Accounting, Financial Reporting, Explainable AI, Earnings Manipulation, Kenya, Anomaly Detection, Modified Jones Model

1. Introduction

The rapid advancement of artificial intelligence (AI) technologies has transformed various sectors, including finance and accounting. Among the myriad applications of AI, its role in detecting creative accounting practices has garnered significant attention from researchers and practitioners alike. Creative accounting, characterized by the manipulation of financial statements to present a more favorable picture of a company's financial health, poses substantial risks to stakeholders, including investors, regulators, and the broader economy. Traditional methods of detection often rely on manual audits and heuristic approaches, which can be time-consuming and prone to human error. In contrast, AI offers the potential for enhanced accuracy and efficiency through data-driven analysis and pattern recognition. This research aims to explore the capabilities of AI in identifying creative accounting practices, examining the methodologies employed, the effectiveness of various AI algorithms, and the implications for regulatory frameworks. By integrating AI into accounting practices, stakeholders may not only improve the integrity of financial reporting but also foster greater trust in the financial markets. This study seeks to contribute to the existing body of knowledge by providing a comprehensive analysis of AI's role in combating creative accounting and highlighting the future prospects of this innovative intersection between technology and finance (Priscilla, 2024).

The findings indicate that AI techniques, such as machine learning and natural language processing, significantly enhance the detection of creative accounting practices, thereby improving overall audit efficiency (Supriadi, 2024). Moreover, the integration of AI in auditing processes not only streamlines the detection of fraudulent activities but also addresses the challenges posed by the increasing complexity of financial data (Adelakun et al., 2024). As AI technologies continue to evolve, their potential to reshape audit practices and enhance financial transparency becomes increasingly evident. The ongoing development of AI tools in auditing signifies a paradigm shift, enabling auditors to address sophisticated financial manipulations with unprecedented speed and precision.This evolution emphasizes the necessity for ongoing research and adaptation of regulatory frameworks to ensure ethical AI deployment in financial auditing.

The integration of Artificial Intelligence (AI) into financial reporting presents a promising frontier for enhancing corporate accountability and detecting creative accounting tendencies among listed corporations in Kenya. This chapter proposes an in-depth examination of how AI technologies can be harnessed to identify financial irregularities and promote transparency in financial disclosures.

AI significantly improves efficiency and accuracy in financial reporting by automating data collection and analysis, thereby reducing human error and enabling real-time monitoring (Krispradana & Mauluddin, 2024).

Research indicates that creative accounting in Kenya is often driven by management compensation schemes, tax management strategies, and insider dealings (Kamau, Namusonge, & Bichanga, 2015). AI tools can be trained to detect such patterns through predictive analytics and statistical models, including regression and correlation analysis. For instance, Kalantari et al. (2023) utilized AI-driven algorithms like the Hartigan-Wong clustering technique to identify distortions in financial statements—an approach that could be adapted for Kenya's context. AI systems can continuously scan vast datasets, flagging anomalies that may signal creative accounting practices such as earnings manipulation or income smoothing (Krispradana & Mauluddin, 2024).

Luan (2024) highlights the application of AI in intelligent auditing, while Polyák (2024) discusses the role of machine learning and deep learning in enhancing reporting accuracy. Although their studies do not focus specifically on Kenya, they provide frameworks applicable to the local corporate environment. Despite these advantages, the chapter will also address ethical and technical challenges, including data privacy, transparency, and regulatory compliance (Krispradana & Mauluddin, 2024). These concerns are critical to ensuring responsible AI deployment.

This chapter aims to provide both theoretical insights and practical recommendations for leveraging AI to detect creative accounting, ultimately strengthening the integrity of financial reporting in Kenya's corporate sector.

2. Literature Review

Creative accounting comprises deliberate manipulations of financial information through the exploitation of flexibilities, ambiguities, and judgmental allowances within accounting standards (Abdullah, 2025). While not always illegal, such practices distort the true financial condition and performance of organizations, enabling managers to achieve desired reporting outcomes. These manipulations may involve timing differences, valuation choices, off–balance sheet arrangements, or subjective estimations, making the boundary between acceptable judgment and deceptive reporting inherently blurred.

The consequences of creative accounting are significant. Misrepresented financial statements can mislead investors, compromise regulatory oversight, and create systemic risks for capital markets. Scandals such as Enron, WorldCom, and Parmalat illustrate the destructive societal and economic consequences of unchecked creative accounting. However, detecting such practices remains challenging due to the complexity, volume, and contextual dependence of modern financial data. Traditional detection methods—rule-based checks, manual audits, and human professional judgment—are limited by informational overload, cognitive biases, and static procedures, underscoring the need for technologically advanced detection tools.

2.1 Artificial Intelligence Capabilities and Knowledge Representation

AI's emergence as a transformative tool for financial forensics arises from its strengths in pattern recognition, anomaly detection, and knowledge representation. Yet, accounting data presents unique challenges due to its hierarchical, semantic, and context-rich nature. For AI to meaningfully detect creative accounting, it must not only identify irregularities but also reason about causality, articulate hypotheses, and provide interpretable findings.

Bennett and Maruyama (2021) provide a useful foundation through their conceptualization of the "Artificial Scientist," an AI agent capable of inductive, deductive, and abductive reasoning; causal analysis; hypothesis testing; and interpretable communication. These capabilities parallel the requirements of forensic accounting, where the goal is not merely identifying anomalies, but explaining the conceptual and procedural mechanisms underlying potential manipulations.

2.2 Foundational AI Paradigms in Creative Accounting Detection

Research in AI is generally organized around three paradigms—logicist, emergentist, and universalist—each offering strengths and limitations in the context of accounting fraud detection.

Logicist AI

Logicist approaches rely on formal rules, symbolic representations, and structured inference. In auditing, such systems can encode accounting standards and regulatory rules, supporting transparent and deterministic checks (Bennett & Maruyama, 2021). Their interpretability aligns well with auditability and regulatory expectations. However, these systems struggle with ambiguous, evolving, or context-dependent manipulation strategies.

Emergentist AI

Emergentist approaches, particularly neural networks and deep learning, excel in learning non-linear and complex patterns from large datasets. Their strength lies in identifying subtle deviations indicative of creative accounting. Nonetheless, emergentist systems often lack interpretability, making it difficult for auditors to understand or justify the basis of detected irregularities (Bennett & Maruyama, 2021).

Universalist AI

Universalist approaches—grounded in Solomonoff induction, Kolmogorov complexity, and algorithmic probability—seek the most compressed, generalizable models of data. According to Bennett (2021), compression correlates with predictive accuracy and generalization. In accounting contexts, manipulations may appear as deviations from highly compressible financial patterns. However, universalist models are often computationally intractable and may produce representations that are not human-interpretable.

Scholars such as Bennett and Maruyama (2021) thus argue for hybrid models integrating the transparency of logicist systems, the adaptive pattern recognition of emergentist models, and the generalization strengths of universalist approaches.

2.3 Traditional Creative Accounting Detection

Traditional approaches to detecting creative accounting have predominantly relied on accrual-based models and financial ratio analysis to uncover managerial manipulation embedded in financial statements. These foundational techniques, developed long before the integration of AI and advanced analytics, remain central to understanding how earnings management has historically been measured and interpreted.

One of the most influential frameworks in this tradition is the Jones Model (1991), which distinguishes nondiscretionary accruals—driven by underlying economic conditions—from discretionary accruals, which may signal managerial manipulation. By modelling accruals as a function of revenue changes and asset levels, the Jones Model provides a baseline for detecting abnormal accounting activity. Yet, the model has been criticized for its inability to adequately capture manipulation through credit sales, as it assumes managers cannot influence revenue recognition on credit—a premise that empirical evidence has repeatedly challenged.

In response to these limitations, Dechow, Sloan, and Sweeney (1995) introduced the Modified Jones Model, which adjusts for changes in credit sales to enhance sensitivity to revenue manipulation. This refinement made the model the most widely applied accrual-based detection tool in academic research. Although it offers improved accuracy, scholars note that it still struggles in environments where firms exhibit volatile earnings patterns or face unique economic cycles, limiting its applicability across diverse sectors.

Earlier models developed by Healy (1985) and DeAngelo (1986) employed simpler approaches, using total accruals or year-to-year changes in accruals to identify manipulation. While easy to implement, these models often oversimplify complex financial behaviors and fail to adjust for firm-specific economic or structural factors. Their weaknesses underscore why later models have attempted to incorporate more nuanced assumptions about managerial incentives and economic conditions.

A significant advancement in manipulation detection came with the development of the Beneish M-Score (1999)—a probabilistic model based on eight financial ratios designed to flag firms likely to be engaging in earnings manipulation, particularly through aggressive revenue recognition. The model gained prominence after identifying Enron as a likely manipulator before its collapse, reinforcing its practical value. Nevertheless, scholars caution that the M-Score may produce elevated false positives in high-growth or financially distressed firms, making contextual interpretation essential.

Further refinements in the literature include the Kasznik (1999) Model, which incorporates expectations of future cash flows and managerial incentives to meet earnings targets. This model is particularly useful for detecting income smoothing behaviors. Despite its conceptual strengths, it shares the broader limitations of accrual-based models, particularly when confronted with firms experiencing significant operational shocks or atypical strategic behavior.

As research evolved, scholars recognized that managers increasingly relied not only on accrual manipulation but also on real earnings management—altering actual business activities to influence reported earnings. Models advanced by Roychowdhury (2006) identify abnormal production costs, discretionary expenses, and cash flow patterns to detect such strategies. Real activity manipulation is often harder to uncover because it involves legitimate operational decisions—such as overproducing inventory or cutting R&D expenditures—that blur the line between strategic management and opportunistic behavior.

Despite their contributions, traditional models exhibit notable limitations. They often rely on static assumptions, assume linear relationships in inherently complex environments, and depend on historical financial data that managers can anticipate and exploit. Moreover, they tend to isolate manipulation within narrow parameters, making them less effective at detecting sophisticated or multi-layered schemes involving off-balance-sheet financing, structured transactions, or cross-period adjustments.

For these reasons, recent scholarship increasingly argues for the integration of traditional statistical models with AI-driven techniques, which can capture nonlinear relationships, dynamic patterns, and hidden interactions. Nonetheless, traditional creative accounting models remain foundational to the field, offering interpretable and theoretically grounded insights into the mechanisms through which firms manipulate financial information.

2.4 Approaches to AI Creative Accounting detection

Compression, Generalization, and Explainability

The role of compression in AI relates directly to the detection of creative accounting. Bennett (2021) asserts that simpler, more compressed models exhibit stronger generalization, making it possible to distinguish normal financial behavior from anomalous, less-compressible patterns. However, as models become more compressed and abstract, they risk becoming less interpretable—creating an “explainability gap” that parallels communication challenges identified in the Fermi Paradox (Bennett, 2021). For auditing applications, this necessitates balancing predictive performance with explainability, ensuring that anomaly detection remains transparent and defensible.

Creative Problem Solving and Adaptive Detection Approaches

Creative accounting evolves in response to new regulations, market pressures, and detection technologies. Detecting such manipulations requires creative problem-solving (CPS) abilities within AI systems. Gizzi et al. (2022) identify four core components of CPS—problem formulation, knowledge representation, knowledge manipulation, and evaluation—that map directly to the needs of forensic accounting.

According to Gizzi et al. (2022), detecting manipulative financial practices begins with problem formulation, which involves framing detection as the identification of anomalies and forming hypotheses about possible manipulative intent. Knowledge representation then requires encoding the relevant financial standards, the semantics of transactions, and typical organizational behaviors to provide a structured basis for analysis (Blue et al., 2025). Once this knowledge is encoded, knowledge manipulation takes place through the use of machine learning algorithms, logical inference, and simulation techniques that help uncover patterns or practices indicative of manipulation. The evaluation stage follows, focusing on assessing the plausibility of detected anomalies, reducing false positives, and enabling adaptive learning so the system improves over time. Gizzi et al. further note that CPS-based models can expand their conceptual spaces, allowing them to discover new forms of manipulation that were not explicitly programmed into the system—a critical capability in adversarial and continuously evolving financial environments.

Simulation, Planning, and Sequential Decision-Making

Simulation-based approaches offer powerful tools for anticipating and understanding creative accounting behaviors. Bennett and Hauser (2013) demonstrate how Markov Decision Processes (MDPs) can model sequential decision-making under uncertainty—a framework that directly translates into auditing. In financial forensics, an AI agent can sequentially evaluate transactions, update risk beliefs, and re-plan audit actions when new information arises.

MDP-based models offer several advanced capabilities in financial detection systems. They can simulate adversarial tactics, enabling auditors to anticipate and model how manipulators might alter their strategies over time. These models also allow for the dynamic optimization of audit plans, adjusting procedures in response to evolving risks and new information. In addition, they can represent interdependent financial events, capturing how one action or transaction influences others across the system. By supporting proactive detection strategies, MDP-based models help auditors identify potential issues before they escalate. Overall, the integration of simulation, cyber-physical systems, and dynamic planning significantly strengthens the robustness and adaptability of modern detection frameworks.

Explainable Artificial Intelligence (XAI) in Auditing

Explainability is indispensable in accounting, where users must be able to justify and contest AI-driven conclusions. Bharati et al. (2023) emphasize that explainability (clarifying why decisions occur) and interpretability (understanding how decisions occur) are both necessary for trust, accountability, and regulatory compliance.

Bharati et al. (2023) highlight several key XAI techniques that enhance the interpretability of AI-driven detection systems. Dimension-reduction methods such as PCA help auditors focus on the most salient features within complex datasets, while feature-selection techniques identify the variables most relevant to anomaly detection. Attention mechanisms further support interpretation by pinpointing the specific data points that influence a model’s decisions. Knowledge distillation is used to simplify highly complex models, making their logic easier to understand, and surrogate models—such as decision trees—offer interpretable approximations of otherwise opaque black-box systems. Despite continued challenges, including contextual complexity, data quality concerns, and the constantly evolving landscape of creative accounting, XAI remains a critical component for effective auditor–AI collaboration and for gaining regulatory trust and acceptance.

Symbol Emergence and Human–AI Communication

Bennett (2021) highlights the importance of symbol emergence—the development of shared abstractions between AI systems and humans. In accounting detection, symbol emergence allows AI to form interpretable representations of concepts such as revenue recognition, asset valuation, or off–balance sheet arrangements. Without alignment between AI-developed symbols and human-understandable concepts, communication failures may occur, limiting auditor trust and oversight.

Therefore, AI systems must be designed to maintain interpretability even as they compress and abstract data representations.

2.5 Organizational, Ethical, and Regulatory Considerations

The successful integration of AI into financial forensics requires more than technical innovation. Bharati et al. (2023) emphasize that the effective adoption of AI in auditing requires rigorous system validation and ongoing evaluation to ensure reliability and accuracy. They also highlight the importance of organizational change management, noting that integrating AI tools demands adjustments in workflows, culture, and governance structures. Training and capacity-building for auditors is essential so that professionals can correctly interpret AI outputs and exercise informed judgment. Equally important is establishing legal clarity regarding liability and due process, ensuring that the use of AI aligns with existing regulatory and ethical frameworks. Transparent communication with stakeholders further supports trust and acceptance of AI-assisted audit processes.

Building on this, Gizzi et al. (2022) argue that continuous learning and robust feedback loops are vital due to the constantly evolving nature of creative accounting. AI systems must be able to update their models, learn from emerging manipulation techniques, and incorporate expert human oversight, ensuring adaptability and long-term effectiveness in detecting financial irregularities.

The literature highlights that AI's promise in detecting creative accounting lies in its capacity for hybrid reasoning, adaptive problem solving, and explainable decision-making. Grounded in the theoretical contributions of Bennett and Maruyama (2021), Bennett (2021), Gizzi et al. (2022), Bharati et al. (2023), and Bennett and Hauser (2013), scholars identify the need for integrated architectures that combine logicist transparency, emergentist learning, and universalist generalization. These must be paired with XAI methodologies, symbol emergence frameworks, and robust organizational processes to ensure trustworthy, comprehensible, and effective detection.

3. Research Methodology

3.1 Research Design

This study adopted a mixed-methods research design that combined quantitative analysis with AI-driven forensic techniques to examine the presence and nature of creative accounting practices. The research focused on four road transport companies operating in Mombasa County. These firms were purposively selected on the basis of data availability, industry relevance, and their compliance with regulatory reporting requirements.

3.2 Data Collection Procedures

Secondary financial data were obtained from audited financial statements, management reports, and statutory filings for each of the four companies, covering a five-year period. These documents provided information on revenues, expenses, accruals, asset valuations, debt levels, and cash flow patterns. Additional qualitative insights were gathered through structured interviews with finance managers and internal auditors to contextualize the quantitative findings and clarify reporting practices.

3.3 AI-Based Analytical Techniques

To enhance detection accuracy, the financial statements were subjected to a suite of AI-driven analytical techniques. Machine learning models, including anomaly-detection algorithms and clustering methods, were employed to identify irregular patterns in accruals, revenue streams, and expenditure behaviors. Explainable AI (XAI) tools—such as feature-importance ranking, surrogate models, and attention mechanisms—were incorporated to interpret model outputs and highlight the specific financial variables contributing to detected anomalies.

Deep-learning models were further used to simulate different manipulation scenarios and assess whether financial patterns aligned more closely with normal operational behavior or with known creative accounting profiles. These AI outputs were compared against results from traditional detection techniques, including the Modified Jones Model and Beneish M-Score, to validate consistency and enhance interpretability.

3.4 Data Analysis

The analysis proceeded in three stages. First, descriptive statistics were computed to summarize financial trends across the four firms. Second, traditional accounting manipulation models were applied to establish baseline indicators of potential creative accounting. Third, AI tools were used to detect deeper, non-linear patterns that may not be captured by classical methods. Cross-validation techniques were employed to ensure model reliability.

4 Data presentation and analysis

The study employed both the Modified Jones Model and AI-driven anomaly detection to assess potential earnings manipulation across four selected corporations. The combination of these approaches allowed for a comprehensive evaluation of both accrual-based deviations and complex, multi-dimensional anomalies in the financial data.

4.1 Modified Jones Model Findings

Application of the Modified Jones Model revealed several periods of potentially aggressive accounting across the four companies under study, highlighting variations in the extent and timing of discretionary accruals. For Company 1, discretionary accruals fluctuated over the five-year period, ranging from moderate negative values in 2015 to smaller positive deviations in 2016. These patterns suggest occasional deviations from expected accrual behavior, reflecting possible managerial attempts to smooth earnings or adjust reported profits in response to internal or external pressures. The most pronounced negative accruals for Company 1 occurred in 2015 and 2018, indicating periods where management may have deferred expenses or accelerated revenue recognition to manipulate earnings or meet financial targets.

Company 2 demonstrated particularly concerning behavior in 2018, with extremely negative discretionary accruals. Such pronounced deviations are indicative of significant accounting adjustments, which could reflect aggressive income smoothing, manipulation of liabilities, or strategic management of reported profits to influence investor perception or comply with contractual obligations such as debt covenants. The magnitude of these accruals raises questions about the reliability of the company's financial reporting during this period.

For Company 3, large negative accruals were observed in both 2015 and 2016. These findings suggest deliberate deferral of expenses or other accrual-based techniques aimed at managing reported earnings. The consistency of negative accruals over consecutive years points to a potential systematic approach to income smoothing, whereby management sought to stabilize profit figures and maintain stakeholder confidence in the company's financial performance.

Company 4 generally exhibited minor deviations across most years, indicating relatively stable and conventional accrual practices. However, 2017 stood out as an anomaly, with unusually high positive accruals. This could signal overstatement of income, aggressive capitalization of expenses, or the recognition of revenues ahead of actual realization. Such behavior warrants further scrutiny, as it may reflect attempts to enhance reported profitability or meet performance benchmarks.

The analysis of discretionary accruals across the four companies underscores the variability of creative accounting practices. While some firms displayed isolated or moderate manipulations, others exhibited more systematic or extreme deviations, highlighting the importance of continuous monitoring and the potential role of advanced detection techniques, including AI-driven models, in identifying complex patterns of earnings management.

4.2 AI/XAI Detection Findings

The AI-driven analysis, implemented using an Isolation Forest model, provided a complementary perspective on the detection of potential creative accounting practices by evaluating patterns across multiple financial variables, including net income, cash flows, and net operating assets. By examining the interrelationships and deviations among these variables, the model was able to identify years that exhibited unusual financial behavior relative to the company's historical performance and peer benchmarks. Specifically, the model flagged Company 2 in 2018 and Company 3 in 2015–2016 as anomalous, closely aligning with the periods of extreme discretionary accruals previously identified by the Modified Jones Model. This convergence suggests that the anomalies detected by the AI model are not isolated artifacts but reflect broader irregularities that span multiple dimensions of financial reporting, reinforcing the reliability of these findings.

In contrast, years in Company 1 and Company 4, although exhibiting some deviations in discretionary accruals according to the Modified Jones Model, were not classified as anomalous by the AI model. This indicates that while these deviations may represent minor or isolated manipulations, they do not form part of a larger pattern of multi-variable irregularities that AI models are designed to detect. The absence of AI-flagged anomalies in these cases underscores the model's ability to focus on systemic deviations rather than individual accounting line-item fluctuations, highlighting the distinction between traditional accrual-based detection and multi-dimensional AI-driven analysis.

The AI-driven findings illustrate the value of machine learning models in enhancing financial forensics. By analyzing complex, non-linear interactions across multiple financial indicators, AI can detect patterns that may elude conventional methods. Moreover, the alignment between AI-detected anomalies and extreme discretionary accruals demonstrates the potential for AI to validate and complement traditional audit techniques, providing auditors with both predictive insights and actionable intelligence for investigating creative accounting practices.

4.3 Comparative Insights

The comparison of the two approaches highlights both convergence and complementarity in detecting creative accounting practices. The most severe cases of potential manipulation—Company 2 in 2018 and Company 3 in 2015–2016—were consistently identified by both the Modified Jones Model and the AI-driven Isolation Forest model. This alignment suggests that these periods represent genuine and substantial deviations from expected financial behavior, providing strong evidence of creative accounting practices. The concurrence of findings across traditional and AI methods reinforces the robustness of the results and demonstrates the value of integrating multiple detection techniques in financial forensics.

However, notable differences emerged in less extreme cases. For instance, moderate discretionary accruals detected by the Modified Jones Model in Company 1 and Company 4 were not classified as anomalies by the AI model. This divergence highlights the fundamental distinction between the two approaches. Traditional accrual-based models focus on theory-driven, interpretable measures of financial deviations, allowing auditors to pinpoint specific accounting entries that may reflect earnings management. In contrast, AI models are designed to capture complex, non-linear relationships and multi-dimensional interactions across various financial variables, flagging anomalies that represent systemic irregularities rather than isolated fluctuations.

This complementarity implies that while the Modified Jones Model remains valuable for identifying and interpreting discrete accrual-based manipulations, AI provides a broader, more holistic perspective by uncovering patterns that may span multiple accounts, years, or interdependent financial indicators. Together, the two approaches offer a comprehensive framework for detecting both overt and subtle forms of creative accounting, enhancing audit effectiveness, accuracy, and the ability to prioritize investigative efforts. By leveraging both methods, auditors and regulators can achieve a deeper understanding of corporate financial behavior, distinguishing between minor deviations and more sophisticated manipulative schemes.

4.4 Discussion of Findings

The findings of this study reveal important insights into the effectiveness of both traditional and AI-driven approaches in detecting creative accounting practices among the selected Kenyan corporations. By combining the Modified Jones Model with AI/XAI techniques, the study provides a nuanced understanding of potential manipulative behaviors and the complementary roles of these methods in financial forensics.

Patterns of Creative Accounting Identified

The application of the Modified Jones Model highlighted periods of potential earnings manipulation across all four firms. In particular, Company 2 in 2018 and Company 3 in 2015–2016 exhibited the most significant discretionary accruals, suggesting aggressive accounting practices aimed at smoothing earnings or deferring expenses. Company 1 and Company 4 showed more moderate deviations, indicating occasional manipulations but of a lesser magnitude. These results corroborate previous research asserting that managers may engage in accrual-based adjustments to meet earnings targets or manage stakeholder expectations (Dechow et al., 1995; Beneish, 1999).

The AI-driven analysis further validated these findings, identifying Company 2 2018 and Company 3 2015–2016 as anomalous years based on multi-variable financial patterns. The convergence of AI and traditional model outputs in these extreme cases strengthens the reliability of the results and demonstrates that AI can effectively detect complex patterns of irregularities across multiple financial dimensions.

Complementarity of AI and Traditional Methods

While both approaches successfully identified severe instances of creative accounting, differences emerged in less extreme cases. For example, moderate discretionary accruals in Company 1 and Company 4 were flagged by the Modified Jones Model but not classified as anomalies by the AI model. This divergence illustrates a key distinction: traditional accrual-based models are sensitive to theoretically defined deviations in accounting entries, providing interpretable indicators of managerial behavior, whereas AI models capture complex, non-linear relationships that span multiple variables and detect broader patterns indicative of systemic irregularities.

This complementarity suggests that an integrated approach—leveraging the interpretability of accrual-based models and the pattern-recognition capabilities of AI—can enhance audit effectiveness. Traditional models provide a baseline understanding of financial deviations, while AI offers adaptive, data-driven insights that may uncover subtle or emergent manipulative practices that are difficult to detect using static models alone.

Implications for Financial Reporting and Audit Practice

The findings underscore the potential for AI to augment traditional auditing processes in Kenya. AI-driven anomaly detection can improve the speed and accuracy of financial oversight by continuously scanning large datasets and highlighting unusual patterns, reducing reliance on manual inspection and heuristic judgment. Moreover, explainable AI techniques ensure that detected anomalies can be interpreted and justified, addressing regulatory and ethical concerns around accountability and transparency.

From a regulatory perspective, the results highlight the need for frameworks that support the responsible integration of AI into financial reporting and auditing. Stakeholders—including auditors, regulators, and corporate governance bodies—must ensure that AI outputs complement human judgment rather than replace it. Continuous training for finance professionals in AI tools, coupled with robust validation and monitoring, is essential to maintain trust in AI-assisted detection mechanisms.

Limitations and Future Research Directions

Despite the insights provided, several limitations warrant consideration. The study focused on four firms in a single sector and geographical region, which may limit the generalizability of findings. Additionally, AI detection is dependent on the quality and completeness of input data; missing or misreported financial information can influence anomaly detection outcomes. Future research could expand the sample size, include diverse sectors, and explore hybrid AI-traditional frameworks tailored to sector-specific reporting practices. Moreover, longitudinal studies could examine how AI detection evolves in response to changes in regulatory requirements and managerial behaviors.

5 Conclusion and recommendation

This study examined the role of Artificial Intelligence (AI) in detecting creative accounting practices within selected Kenyan corporations, comparing AI-driven techniques with traditional accrual-based models such as the Modified Jones Model and the Beneish M-Score. The findings demonstrate that AI has considerable potential to enhance the detection of financial irregularities, particularly in identifying complex and non-linear patterns that may not be captured by conventional methods. Extreme cases of potential earnings manipulation, such as Company 2 in 2018 and Company 3 in 2015–2016, were consistently flagged by both AI and traditional approaches, confirming the reliability and complementarity of these methods.

Traditional accrual-based models continue to provide valuable, interpretable indicators of managerial behavior, while AI contributes by detecting broader anomalies across multiple financial dimensions. Integrating these approaches allows auditors to benefit from both the theoretical grounding of classical models and the adaptive, data-driven insights offered by AI, thereby improving the robustness, accuracy, and comprehensiveness of creative accounting detection.

The study further highlights that AI can significantly enhance audit efficiency, reduce human error, and support real-time monitoring of financial data. Explainable AI (XAI) tools, which clarify the rationale behind AI decisions, are essential in promoting transparency, regulatory compliance, and stakeholder trust. However, the successful adoption of AI requires more than technical capability. Organizations must invest in training auditors to interpret AI outputs correctly, implement robust system validation, and develop clear governance and regulatory frameworks that ensure ethical and responsible use of AI in financial reporting.

Based on these insights, it is recommended that organizations adopt hybrid detection approaches that combine traditional accounting models with AI-driven analytical tools. Such integration would leverage the strengths of both methods, provide interpretable, theory-based insights while capture complex, emergent patterns of manipulation. Auditors should receive continuous professional development on AI applications, machine learning, and XAI techniques to fully utilize these tools in their work. Regulators should also establish clear guidelines on the deployment of AI in auditing, including standards for data quality, system validation, accountability, and audit trails.

Organizations should prioritize accurate, complete, and standardized financial reporting, as reliable data forms the foundation for effective AI analysis. Additionally, AI systems should be designed to adapt over time, updating models in response to evolving manipulative practices, ensuring proactive rather than reactive detection. Finally, continued research and innovation are encouraged, including expanding AI applications to different sectors, exploring sector-specific models, and evaluating the longitudinal performance of AI-based detection systems.

In conclusion, integrating AI into auditing and financial reporting represents a transformative opportunity to strengthen corporate governance, enhance financial transparency, and foster stakeholder trust. By combining the insights of traditional accrual-based models with the adaptive power of AI, organizations in Kenya can more effectively identify and address creative accounting, ensuring the integrity and reliability of financial reporting in an increasingly complex and dynamic business environment.

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