American Journal of Economics and Business Management
Vol. 8 Issue 8 | pp. 4127-4141 | ISSN: 2576-5973
Available online @ https://www.globalresearchnetwork.us/index.php/ajebm

Article

Effectiveness of Artificial Intelligence in Detecting Financial Statement Fraud

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Abstract: This study examined the effectiveness of Artificial Intelligence (AI) in detecting financial statement fraud in Port Harcourt Metropolis, Nigeria, with a focus on Natural Language Processing (NLP) techniques and Model Interpretability frameworks. Using a descriptive research design, data were collected from 400 professionals across 25 commercial banks, two microfinance banks, and one specialized financial service provider. Key stakeholders included internal auditors, risk management teams, financial analysts, senior bank executives, data scientists, and regulatory bodies. A purposive sampling technique was employed, and data were gathered through structured questionnaires and semi-structured interviews. Findings revealed that AI-driven fraud detection enhances audit credibility, risk identification, and financial transparency. Specifically, interpretable AI models, such as SHAP and LIME, significantly improved auditor confidence and fraud risk assessment. However, concerns were raised about the reliability of some NLP techniques, such as text mining. Descriptive statistics (Mean and Standard Deviation) were used to analyze survey responses, while content analysis was applied to interview data. Reliability was assessed using Cronbach's Alpha (≥ 0.7), and test-retest reliability confirmed instrument consistency. The study concluded that balancing AI model accuracy with interpretability is crucial for fraud detection effectiveness. It recommended that banks and regulatory bodies invest in explainable AI models and provide continuous training for financial professionals to enhance their understanding and application of AI-based fraud detection. The findings highlight the growing relevance of AI in financial fraud prevention, emphasizing the need for transparent and trustworthy AI solutions in the banking sector.

Keywords: Artificial intelligence, financial statement fraud, natural language processing, model interpretability, fraud detection

Citation: Chinumezi, T. J, Ichenda, O. V, Innocent E & Florence, O. Effectiveness of Artificial Intelligence in Detecting Financial Statement Fraud. American Journal of Economics and Business Management 2025, 8(8), 4127-4141.

Received: 10th May 2025
Revised: 16th Jun 2025
Accepted: 24th Jul 2025
Published: 20th Aug 2025

1. Introduction

Detecting financial statement fraud is a critical challenge in the financial world, posing significant risks to investors, regulatory bodies, and the integrity of financial markets. The complexity and sophistication of financial fraud have necessitated the development of advanced tools and techniques to identify fraudulent activities effectively. In recent years, artificial intelligence (AI) has emerged as a powerful ally in this battle, offering capabilities that far surpass traditional methods of fraud detection [1], [2]. Artificial intelligence encompasses a variety of technologies, including machine learning, natural language processing, and data mining, which can be leveraged to detect anomalies and patterns indicative of fraud. Macas, stated that these AI systems can process vast amounts of data at unprecedented speeds, allowing for the real-time analysis of financial statements. By employing machine learning algorithms, AI can learn from historical fraud patterns and apply this knowledge to new data, continually improving its accuracy and effectiveness in identifying irregularities [3]. One of the primary advantages of AI in detecting financial statement fraud is its ability to analyze unstructured data. Traditional fraud detection methods rely heavily on structured data, such as financial ratios and transaction records, which may miss subtle signs of fraud hidden in unstructured data like emails, audit reports, and social media posts [4]. AI's natural language processing capabilities enable it to interpret and analyze this unstructured data, uncovering hidden relationships and potential red flags that might indicate fraudulent activity.

Furthermore, AI's predictive analytics capabilities are instrumental in preemptively identifying potential fraud. Williamson et al. stated that by analyzing historical data and identifying patterns associated with past fraudulent activities, AI can predict the likelihood of future fraud occurrences [5], [6]. This predictive approach allows organizations to implement proactive measures, mitigating risks before they escalate into significant issues. For instance, AI can flag unusual transactions or discrepancies in financial statements for further investigation, thereby enhancing the efficiency of audit processes and reducing the reliance on manual, time-consuming methods [7], [8]. Another critical aspect of AI's effectiveness in fraud detection is its ability to continuously learn and adapt. Unlike static rule-based systems, AI algorithms evolve over time, learning from new data and adapting to emerging fraud tactics. This continuous learning capability ensures that AI systems remain effective even as fraudsters develop more sophisticated methods to evade detection. Additionally, AI can integrate multiple data sources and cross-reference information, providing a more comprehensive view of potential fraud risks. The integration of AI in fraud detection also offers significant cost savings and operational efficiencies. Pinzón et al stated that traditional audit processes are labor-intensive and costly, often requiring extensive human resources and time [9]. AI systems can automate much of this work, reducing the need for large audit teams and allowing human auditors to focus on more complex and judgment-based tasks. This automation not only cuts costs but also enhances the speed and accuracy of fraud detection efforts.

Despite these advantages, the adoption of AI in detecting financial statement fraud is not without challenges. The effectiveness of AI systems heavily depends on the quality and quantity of data available for analysis [10]. Poor data quality, incomplete datasets, or biased data can lead to inaccurate predictions and false positives, undermining the reliability of AI-driven fraud detection. Moreover, the complexity of AI algorithms can sometimes make it difficult for auditors and regulatory bodies to understand and trust the results, a phenomenon known as the "black box" problem. Ensuring transparency and interpretability of AI systems is crucial for gaining the trust of stakeholders [11].

Statement of the Problem

Detecting financial statement fraud is an ongoing challenge that has significant implications for the credibility and stability of financial markets. Traditional methods of fraud detection, often reliant on manual audits and rule-based systems, have proven insufficient in addressing the growing sophistication and volume of fraudulent activities [12]. Consequently, there has been a growing interest in the potential of artificial intelligence (AI) to enhance the effectiveness of fraud detection. However, despite its promise, the implementation of AI in this domain is fraught with challenges and limitations that need thorough examination. One of the primary problems is that financial statement fraud is becoming increasingly complex, making it difficult for conventional methods to keep up. Rangaraju stated that traditional techniques typically involve checking for compliance with established rules and norms, which fraudsters can easily manipulate or circumvent. As fraud schemes evolve, they often leave fewer overt clues and generate data patterns that are not easily detectable by standard analytical tools. AI, with its advanced pattern recognition capabilities and ability to process large datasets, offers a promising solution [13]. Yet, the question remains: how effective is AI in reliably identifying these sophisticated fraud schemes?

A significant issue with the effectiveness of AI in fraud detection lies in the quality and availability of data. AI systems require large volumes of high-quality data to learn and make accurate predictions. In the financial sector, data can often be incomplete, noisy, or biased, which can compromise the accuracy of AI models. Additionally, the data used for training AI systems often reflects historical fraud patterns. While this helps in identifying known fraud schemes, it might not be as effective in recognizing novel, emerging fraud techniques that have no historical precedent. Another problem is the "black box" nature of many AI models. AI systems, particularly those based on deep learning, can be highly complex and lack transparency. Kumar and Sergeeva stated that this opaqueness can lead to a lack of trust among auditors, regulators, and other stakeholders who are accustomed to traditional, more understandable methods of fraud detection [14]. The inability to explain how an AI system arrived at a particular conclusion makes it difficult to validate and trust its findings. This lack of transparency can hinder the adoption and effectiveness of AI in practical, regulatory environments where accountability and understanding are crucial.

Furthermore, the dynamic nature of fraud requires AI systems to be highly adaptable and continuously updated. Fraudsters constantly develop new techniques to bypass detection mechanisms. AI models need to be retrained and updated regularly with new data to stay relevant and effective [15]. This ongoing need for adaptation poses significant logistical and operational challenges, including the need for continuous monitoring and the integration of new data sources. Ensuring that AI systems remain up-to-date and capable of detecting the latest fraud techniques requires substantial resources and expertise. The cost and complexity of implementing AI-based fraud detection systems also pose considerable barriers. Developing and maintaining sophisticated AI models is resource-intensive, requiring significant investments in technology, skilled personnel, and infrastructure. Fritz-Morgenthal et al. stated that smaller organizations or those with limited resources may find it challenging to adopt AI solutions, potentially creating a gap between larger firms that can afford such technologies and smaller ones that cannot. In addition to these technical and operational issues, there are also ethical and regulatory concerns. The deployment of AI in financial fraud detection must comply with regulatory standards and protect sensitive financial data. Ensuring that AI systems are designed and used ethically, without introducing biases or unfair practices, is a significant challenge. Regulatory frameworks must evolve to address the unique challenges posed by AI, balancing the need for effective fraud detection with the protection of individual rights and maintaining market integrity.

Aim and objectives of the study

The main aim of the study was to determine the effectiveness of artificial intelligence in detecting financial statement fraud. The specific objectives of the study was to;

1. Determine the effect of Natural Language Processing on Detecting Financial Statement Fraud among financial institutions in Port Harcourt, Nigeria
2. Ascertain the effect of Model Interpretability on Detecting Financial Statement Fraud among financial institutions in Port Harcourt, Nigeria

Research Questions

1. What is the effect of Natural Language Processing in detecting financial statement fraud among financial institutions in Port Harcourt, Nigeria?
2. What is the effect of Model Interpretability in detecting financial statement fraud among financial institutions in Port Harcourt, Nigeria?

Literature Review

Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that focuses on the interaction between computers and human languages [16]. It enables machines to understand, interpret, and generate human language in a way that is both meaningful and useful. NLP combines computational linguistics rule-based modeling of human language with statistical, machine learning, and deep learning models. These technologies allow computers to process human language data and perform a variety of language-related tasks. The development of NLP has been driven by the increasing availability of textual data and the need to automate the analysis of this data. Buhrmester et al. stated that one of the primary goals of NLP is to enable computers to read and understand human languages [17], [18]. This involves several key tasks, including tokenization, which breaks down text into smaller units like words or phrases; part-of-speech tagging, which identifies the grammatical categories of words; and parsing, which determines the syntactic structure of a sentence. These foundational tasks are crucial for more complex NLP applications.

Sentiment analysis is one of the most widely used applications of NLP. It involves determining the sentiment expressed in a piece of text, such as whether a product review is positive, negative, or neutral. Sentiment analysis uses machine learning algorithms trained on large datasets of annotated text to identify sentiment-bearing words and phrases and assess the overall sentiment of new texts [19]. This application is valuable in various fields, including market research, customer service, and social media monitoring, where understanding public sentiment can provide actionable insights. Another important application of NLP is named entity recognition (NER), which involves identifying and classifying proper nouns in text into predefined categories such as names of people, organizations, locations, and dates. Gautam stated that ner is essential for information extraction, enabling systems to pull out relevant information from large text corpora efficiently [20]. For instance, in the financial industry, NER can be used to automatically extract key information from financial reports, news articles, and other documents, thereby saving time and reducing the risk of human error. Machine translation is another significant area where NLP has made substantial strides. Early machine translation systems relied on rule-based approaches, but modern systems predominantly use statistical and neural network-based methods. These methods have greatly improved the accuracy and fluency of translations. Neural machine translation, in particular, leverages deep learning models to translate entire sentences at once, rather than word by word, resulting in more coherent and contextually appropriate translations. Services like Google Translate have become widely used, making information accessible across language barriers [21].

Question answering systems represent another advanced application of NLP. Adaga et al. stated that these systems are designed to provide precise answers to user queries by understanding the context and semantics of the question. They can be used in various domains, from customer support chatbots to virtual assistants like Siri and Alexa. These systems combine multiple NLP techniques, including information retrieval, where the system searches through a large corpus of documents to find relevant information, and natural language understanding, which allows the system to comprehend the meaning and intent behind the user's query. Text summarization is a challenging but highly useful NLP task that involves generating a concise summary of a longer document while preserving its main ideas. There are two main approaches to text summarization: extractive and abstractive [22]. Extractive summarization involves selecting and concatenating the most important sentences from the original text, while abstractive summarization generates new sentences that convey the key points, often using advanced machine learning techniques to produce more natural and human-like summaries. NLP also plays a crucial role in speech recognition and synthesis, enabling applications like voice-activated assistants and automated transcription services. Speech recognition involves converting spoken language into text, which can then be processed by NLP systems for further analysis or response generation. Speech synthesis, on the other hand, involves generating spoken language from text, allowing machines to communicate with humans in a natural and understandable way [23].

Model Interpretability

Model interpretability refers to the degree to which a human can understand the cause and effect in a machine learning model. As artificial intelligence (AI) and machine learning (ML) systems become increasingly integrated into critical decision-making processes, the need for interpretable models grows. This requirement stems from the necessity to ensure that models are not only accurate but also transparent, explainable, and accountable. One of the key aspects of model interpretability is the ability to explain how a model makes decisions. In traditional linear models, interpretability is relatively straightforward because the relationship between input variables and the output is clear and direct. However, modern machine learning models, especially deep learning models, are often much more complex. Afjal et al. stated that these models involve numerous layers of non-linear transformations and vast numbers of parameters, making it challenging to trace the path from input to output.

The importance of model interpretability is particularly pronounced in high-stakes fields such as healthcare, finance, and criminal justice. For instance, in healthcare, AI models are used to diagnose diseases, recommend treatments, and predict patient outcomes. If a model makes an incorrect prediction, understanding the reasoning behind it can help healthcare professionals identify potential errors in the data or the model itself, ensuring that patient safety is not compromised. Similarly, in finance, interpretability is crucial for compliance with regulatory standards and for maintaining the trust of stakeholders when models are used to make decisions about credit scoring, fraud detection, or investment strategies. There are several approaches to improving the interpretability of machine learning models. Blanke stated that one approach is to use inherently interpretable models, such as decision trees, linear regression, or logistic regression. These models are simpler and provide clear insights into how inputs are related to outputs. However, they often sacrifice accuracy for interpretability, especially when dealing with complex datasets. Another approach involves developing methods to interpret complex models post hoc. Techniques such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) are widely used for this purpose. LIME approximates the complex model locally with an interpretable model to explain individual predictions. SHAP, on the other hand, assigns each feature an importance value for a particular prediction based on cooperative game theory. These methods help in understanding the contribution of each feature to a prediction, thereby making complex models more transparent.

Visualization tools also play a significant role in model interpretability. Bao and Hilary stated that visualizations such as feature importance plots, partial dependence plots, and individual conditional expectation plots help to elucidate the relationships between features and predictions. These tools enable users to see how changes in input variables affect the output, providing insights into the model's behavior. Despite these advances, there are still significant challenges in achieving model interpretability. One major challenge is the trade-off between accuracy and interpretability. Often, more complex models yield higher accuracy but are harder to interpret, while simpler models are more interpretable but less accurate. Balancing this trade-off requires careful consideration of the specific application and the acceptable level of interpretability. Another challenge is ensuring that interpretations are accurate and reliable. Misinterpretation of model outputs can lead to incorrect conclusions and potentially harmful decisions. Therefore, it is essential to validate interpretability methods and ensure that they provide faithful representations of the model's decision-making process. Ethical considerations also underscore the importance of model interpretability. Macas, stated that as AI systems make decisions that impact individuals' lives, it is crucial to ensure that these decisions are fair and unbiased. Interpretability helps in identifying and mitigating biases in models, promoting fairness and accountability. Moreover, transparent models foster trust among users, stakeholders, and regulatory bodies, which is vital for the broader acceptance and adoption of AI technologies.

Financial Statement Fraud

Financial statement fraud involves the deliberate misrepresentation of a company's financial position, often to deceive investors, creditors, and regulatory authorities. This type of fraud can take various forms, such as falsifying revenues, understating expenses, inflating assets, or concealing liabilities. The primary motive behind financial statement fraud is typically to present a more favorable picture of the company's financial health than is accurate, often to boost stock prices, secure loans, or meet financial targets. The consequences of financial statement fraud are severe, impacting not only the company involved but also its stakeholders and the broader financial market. Kumar and Sergeeva stated that investors rely on accurate financial statements to make informed decisions. When these statements are manipulated, it can lead to substantial financial losses, as seen in high-profile cases like Enron and WorldCom. These incidents not only caused significant financial harm to investors but also undermined public trust in financial markets and led to increased regulatory scrutiny. Detection of financial statement fraud is notoriously challenging due to the sophistication of modern fraud schemes. Fraudsters often employ complex methods to disguise their activities, making it difficult for traditional auditing techniques to uncover discrepancies. Internal controls and audits are the first line of defense, but they can be bypassed by collusion among employees or management. This necessitates more advanced tools and methodologies to effectively detect and prevent fraud.

One of the primary methods for detecting financial statement fraud is forensic accounting, which involves a detailed examination of financial records and transactions. Pinzón et al. stated that forensic accountants look for red flags such as unexplained discrepancies between reported and actual performance, unusual accounting entries, or inconsistencies in supporting documentation. This process is thorough and often requires a deep understanding of both accounting principles and the business context. Technological advancements have also enhanced the ability to detect financial statement fraud. Data analytics and artificial intelligence (AI) are increasingly used to identify patterns and anomalies that might indicate fraudulent activity. Machine learning algorithms, for example, can analyze large datasets to detect unusual patterns or trends that human auditors might miss. These technologies can process and cross-reference vast amounts of data from various sources, improving the chances of identifying fraudulent activities. Despite these advancements, several challenges remain in detecting financial statement fraud. One significant challenge is the dynamic nature of fraud schemes. Shahbazi and Byun, stated that as detection methods evolve, so do the techniques used by fraudsters to evade them. This cat-and-mouse game requires continuous updating and refinement of detection methodologies. Additionally, the quality and integrity of the data used for analysis are crucial. Incomplete or inaccurate data can lead to false positives or negatives, undermining the effectiveness of fraud detection efforts.

The regulatory environment also plays a critical role in preventing and detecting financial statement fraud. Regulatory bodies such as the Securities and Exchange Commission (SEC) in the United States enforce rules and guidelines that companies must follow in their financial reporting. These regulations are designed to promote transparency and accountability. However, compliance alone is not enough to prevent fraud; effective enforcement and the imposition of penalties for violations are also necessary to deter fraudulent activities. Corporate governance is another crucial factor in combating financial statement fraud. Strong governance practices, including an independent board of directors, a robust internal control system, and a culture of ethical behavior, can significantly reduce the risk of fraud. When company leadership is committed to transparency and integrity, it sets a tone that permeates the entire organization, making it harder for fraudulent activities to take root. Education and training are essential components in the fight against financial statement fraud. Ensuring that employees at all levels understand the importance of accurate financial reporting and are trained to recognize potential signs of fraud can create a more vigilant and proactive workforce. Regular training sessions and clear communication about the consequences of fraud can reinforce a culture of honesty and accountability.

Theoretical Review

Machine Learning Theory

Machine Learning (ML) theory underpins the effectiveness of artificial intelligence (AI) in detecting financial statement fraud by providing the foundational algorithms and techniques that enable AI systems to learn from data, identify patterns, and make predictions. The relationship between ML theory and fraud detection is multifaceted, involving various aspects such as model training, feature selection, anomaly detection, and continuous learning. At its core, ML theory involves the development and understanding of algorithms that can learn from and make predictions based on data. Rangaraju stated that these algorithms can be broadly categorized into supervised learning, unsupervised learning, and semi-supervised learning. In the context of financial statement fraud detection, supervised learning algorithms are often employed to classify transactions or financial statements as fraudulent or non-fraudulent. These algorithms are trained on labeled datasets containing examples of both fraudulent and legitimate financial activities. By learning from these examples, the model can generalize to new, unseen data and identify potential fraud. Feature selection, a crucial aspect of ML theory, significantly enhances the effectiveness of AI in fraud detection. Bouchama, and Kamal stated that the choice of features, or variables, used by the ML model directly impacts its performance. In financial fraud detection, relevant features might include unusual patterns in revenue recognition, discrepancies between reported and actual performance, sudden changes in financial ratios, and inconsistencies in financial documentation. ML algorithms can analyze large datasets to identify which features are most indicative of fraud, thus improving the accuracy and reliability of fraud detection models.

Anomaly detection is another critical area where ML theory contributes to fraud detection. Unsupervised learning algorithms, such as clustering and dimensionality reduction techniques, can be used to detect anomalies or outliers in financial data. These anomalies might indicate fraudulent activities that do not conform to the typical patterns of legitimate transactions. By identifying these outliers, ML models can flag suspicious transactions or financial statements for further investigation. This is particularly useful in cases where labeled datasets are not available, and the goal is to detect previously unknown fraud patterns. The concept of overfitting and regularization, central to ML theory, also plays a significant role in the effectiveness of AI-based fraud detection systems. Gautam stated that overfitting occurs when a model learns the noise in the training data rather than the underlying patterns, leading to poor performance on new, unseen data. Regularization techniques, such as L1 and L2 regularization, help prevent overfitting by penalizing overly complex models. In fraud detection, avoiding overfitting is crucial because it ensures that the model can generalize well to new instances of fraud that were not present in the training data. Continuous learning and model updating are essential components of ML theory that enhance AI's effectiveness in fraud detection. Financial fraud tactics evolve over time, necessitating models that can adapt to new patterns and behaviors. Online learning algorithms and techniques such as transfer learning enable models to update incrementally as new data becomes available. This continuous adaptation helps maintain the model's accuracy and relevance in detecting emerging fraud schemes.

Moreover, the interpretability of ML models, a topic of increasing importance in ML theory, is critical in the context of financial fraud detection. Buhrmester et al stated that regulators, auditors, and other stakeholders often require explanations for the decisions made by AI systems. Techniques such as feature importance analysis, SHAP values, and LIME provide insights into how models make predictions, thereby enhancing transparency and trust in the AI system. Understanding the reasoning behind a model's predictions is particularly important in financial contexts, where decisions based on model outputs can have significant legal and economic implications. Furthermore, ensemble methods, another area of ML theory, improve the robustness and accuracy of fraud detection systems. Techniques like bagging, boosting, and stacking combine multiple models to produce a single, more reliable prediction. By aggregating the strengths of different models, ensemble methods can reduce the likelihood of false positives and negatives, thereby increasing the overall effectiveness of fraud detection (Bouchama & Kamal. The scalability of ML algorithms, grounded in ML theory, is also vital for processing the vast amounts of financial data generated by organizations. Fritz-Morgenthal et al. stated that techniques such as distributed computing and parallel processing enable ML models to handle large datasets efficiently, ensuring timely detection of fraudulent activities. This scalability is crucial for real-time fraud detection systems that need to analyze data streams continuously and respond to potential threats promptly.

Empirical Studies

Ahmed and Mahmood examined artificial intelligence techniques in fraud detection and prevention. This review synthesized the use of artificial intelligence techniques in fraud detection and prevention across different sectors, including finance, healthcare, and e-commerce. The study identified neural networks, decision trees, and genetic algorithms as prominent AI techniques applied in these domains. The review concluded that AI techniques significantly enhance fraud detection capabilities by analyzing large datasets and identifying complex patterns indicative of fraudulent behavior. However, the effectiveness of AI models relies on the quality of data and continuous model refinement. The authors recommended further research to develop hybrid AI systems that integrate multiple techniques to improve detection accuracy and reduce false positives. They also emphasized the importance of interpretability and transparency in AI models to gain trust and acceptance in practical applications.

Wang et al. examined deep learning for financial fraud detection. This review focused on the application of deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), in financial fraud detection. The study found that deep learning models exhibit superior performance in identifying complex fraud patterns compared to traditional machine learning methods. The review concluded that deep learning shows promise in enhancing fraud detection accuracy by leveraging its ability to learn intricate patterns from raw data. However, challenges such as interpretability and scalability need to be addressed for practical deployment. The authors recommended further exploration of explainable AI techniques to enhance the interpretability of deep learning models in fraud detection. They also suggested research into scalable architectures that can handle large-scale financial datasets efficiently.

Włodarczyk et al. examined application of artificial intelligence in fraud detection and prevention in the banking sector. This study investigated the application of artificial intelligence in fraud detection and prevention specifically within the banking sector. The research highlighted the effectiveness of AI techniques, such as machine learning and neural networks, in detecting fraudulent transactions and improving security measures. The study concluded that AI plays a crucial role in mitigating fraud risks in banking operations by continuously analyzing transaction data and identifying suspicious activities in real-time. However, it emphasized the importance of robust data governance and privacy protection in AI-powered fraud detection systems. The authors recommended that banks invest in AI technologies and collaborate with fintech companies to develop innovative fraud detection solutions. They also stressed the need for ongoing monitoring and evaluation of AI models to ensure their effectiveness and compliance with regulatory requirements.

Whitrow et al. studied that credit card fraud detection using artificial intelligence techniques. This study applied machine learning techniques to detect credit card fraud, using various algorithms such as decision trees and neural networks. The research found that ensemble methods, combining multiple algorithms, performed better than individual models. The study concluded that AI techniques significantly enhance the accuracy of fraud detection systems, particularly when using ensemble methods. The complexity of fraud patterns requires sophisticated approaches to maintain high detection rates while minimizing false positives. The authors recommended further exploration of ensemble methods and hybrid models to improve detection rates. Additionally, they emphasized the importance of continuous model updating to adapt to evolving fraud tactics. Abdallah, et al. examined fraud detection system: a survey. This comprehensive survey reviewed various AI techniques used in fraud detection across different domains. The study highlighted that neural networks and support vector machines (SVMs) were among the most effective methods [24]. The survey concluded that no single AI technique is universally superior; instead, the effectiveness of a method depends on the specific context and nature of the fraud being addressed. Combining multiple techniques often yields better results. The authors recommended that future research should focus on developing adaptive systems that can learn and evolve with new fraud patterns. They also suggested the integration of AI with human expertise for optimal results [25].

Ngai et al. examined the application of data mining techniques in financial fraud detection: a classification framework and an academic review of literature. This study classified and reviewed various data mining techniques used in financial fraud detection. It found that AI techniques, such as decision trees, neural networks, and Bayesian networks, are highly effective in identifying fraudulent activities. The study concluded that AI and data mining techniques significantly improve the accuracy and efficiency of fraud detection systems. However, the success of these techniques depends on the quality and quantity of data available. The authors recommended that organizations invest in comprehensive data collection and preprocessing to enhance the effectiveness of AI models [26]. They also suggested ongoing collaboration between academic researchers and industry practitioners to develop more robust fraud detection systems.

West and Bhattacharya examined intelligent financial fraud detection: a comprehensive review. This review analyzed various intelligent techniques, including AI and machine learning, used for financial fraud detection. It found that AI techniques, particularly machine learning, have a high potential for detecting complex and evolving fraud patterns. The review concluded that AI significantly enhances the ability to detect financial fraud by identifying subtle and sophisticated fraudulent behaviors that traditional methods might miss. The authors recommended the development of hybrid systems that combine AI with traditional methods to leverage the strengths of both approaches . They also stressed the importance of real-time data processing to improve detection speed and accuracy.

Phua studies a comprehensive survey of data mining-based fraud detection research. This survey reviewed various data mining techniques, including AI-based methods, for fraud detection. The study found that AI techniques, such as neural networks and support vector machines, are effective in detecting different types of fraud, including credit card and insurance fraud. The survey concluded that AI and data mining techniques are essential for developing effective fraud detection systems. However, the effectiveness of these techniques varies depending on the type and context of the fraud. The authors recommended further research into the application of AI in emerging areas of fraud and the development of adaptive systems that can evolve with changing fraud patterns. They also suggested greater emphasis on integrating AI with domain-specific knowledge to enhance detection accuracy.

2. Materials and Methods

This study adopted a descriptive research design to examine the effectiveness of artificial intelligence in detecting financial statement fraud in Port Harcourt Metropolis, Nigeria. It focused on 25 commercial banks, two microfinance banks, and one specialized financial service provider, targeting key stakeholders such as internal auditors, risk management teams, financial analysts, senior bank executives, data scientists, and regulatory bodies in Port Harcourt metropolis. A sample of 400 was adopted, while purposive sampling technique was used to select professionals directly involved in fraud detection. Data were collected through a four rating scale structured questionnaire tagged *'Effectiveness of Artificial Intelligence in Detecting Financial Statement Fraud Questionnaire'* and semi-structured interviews, focusing on NLP techniques (e.g., sentiment analysis, text mining) and model interpretability frameworks (e.g., SHAP, LIME). Secondary data were sourced from financial reports, regulatory guidelines, and academic studies. For reliability, the internal consistency of the questionnaire was assessed using Cronbach's Alpha, with a threshold of 0.7 considered acceptable. Additionally, test-retest reliability was performed by administering the questionnaire to a subset of respondents at two different times, ensuring consistency in responses. The study ensured confidentiality, voluntary participation, and informed consent, maintaining ethical standards in data collection and analysis. Mean and Standard Deviation was used to summarize survey responses at criterion mean of 2.5, while content analysis was applied to interview data to identify recurring themes.

Data Analysis

Professionals from the banking industry in Port Harcourt Metropolis who work in financial fraud detection were included in the study. With the largest group being 41–50 years old (26.56%), followed by 18–30 years old (25.52%), 31–40 years old (24.74%), and 51 years and above (23.18%), the age distribution was well balanced and showed a mix of mid-career and experienced professionals. With 49.22% of women and 50.78% of men, gender representation was almost equal, indicating inclusivity in fraud detection roles.

Table 1. Analysis of Demographic Variables

Variable	Category	Frequency	Percentage (%)
Age Group	18-30 years	98	25.52
	31-40 years	95	24.74
	41-50 years	102	26.56
	51 years and above	89	23.18
Gender	Male	195	50.78
	Female	189	49.22
	BSc/HND	194	50.52
	MSc/MBA	113	29.43
	PhD	61	15.89
	Other	16	4.17
Stakeholder Group	Internal Auditors	62	16.15
	Risk Management Teams	66	17.19
	Financial Analysts	55	14.32
	Senior Bank Executives	56	14.58
	Data Scientists	80	20.83
	Regulatory Bodies	65	16.93

Total	384	100

As seen by the educational backgrounds of 50.52% with a BSc/HND, 29.43% with an MSc/MBA, and 15.89% with a PhD, financial auditing requires a high level of intellectual expertise. With a focus on AI-driven fraud detection, data scientists (20.83%) were the most represented stakeholder group. Regulatory Bodies (16.93%), Internal Auditors (16.15%), Senior Bank Executives (14.58%), Risk Management Teams (17.19%), and Financial Analysts (14.32%) were other important groupings. This distribution highlights how different professions work together to detect financial crime.

3. Results and Discussion

Data Analysis and Results

Research Question One: What is the effect of Natural Language Processing in detecting financial statement fraud?

The findings suggest general agreement on the effectiveness of Natural Language Processing (NLP) in detecting financial statement fraud, with a grand mean of 2.66. Sentiment analysis (mean = 2.73) and machine learning-based NLP models (mean = 2.55) were seen as effective in fraud detection. NLP-driven fraud detection reducing human bias (mean = 2.69) and its integration into audits (mean = 2.84) were also positively viewed. However, there was disagreement regarding NLP techniques like text mining (mean = 2.42) and NLP models' reliability in detecting inconsistencies (mean = 2.82). Overall, respondents generally supported NLP's role in fraud detection but saw limitations in some areas (Table 2).

Table 2. Descriptive Statistics on the effect of Natural Language Processing in detecting financial statement fraud

S/N	Items(n=384)	SA	A	D	SD	Mean	Std.	Remark
1	NLP techniques (e.g., sentiment analysis, text mining) improve the detection of fraudulent financial statements.	66	114	114	90	2.42	1.08	**Disagreed**
2	Sentiment analysis of financial reports helps in identifying fraudulent activities.	120	105	95	64	2.73	1.07	**Agreed**
3	Machine learning-based NLP models enhance the accuracy of fraud detection in financial statements.	100	100	95	89	2.55	1.11	**Agreed**
4	NLP-driven fraud detection reduces human biases in financial statement analysis.	110	115	90	69	2.69	1.07	**Agreed**
5	The integration of NLP in financial audits leads to better fraud detection outcomes.	130	110	95	49	2.84	1.03	**Agreed**
6	NLP models are reliable in detecting inconsistencies in financial disclosures.	140	92	96	56	2.82	1.08	**Disagreed**
7	NLP can identify patterns of deception in financial statements that traditional methods may overlook.	92	101	112	79	2.54	1.07	**Agreed**
	Grand Mean					**2.66**	**1.07**	**Agreed**

Research Question Two: What is the effect of Model Interpretability in detecting financial statement fraud?

The table 3 highlights the positive effect of model interpretability in detecting financial statement fraud using Natural Language Processing (NLP). The mean scores range from 2.53 to 2.74, indicating general agreement with the statements. Standard deviations are consistent, reflecting moderate agreement across responses. The "Grand Mean" of 2.67 shows a strong consensus that interpretable AI models enhance fraud detection by improving credibility, boosting auditor confidence, and aiding in identifying fraud risks. The lack of interpretability is seen as a challenge in investigations. Overall, the findings suggest that model interpretability plays a key role in effective fraud detection.

Table 3. Descriptive Statistics on the effect of Natural Language Processing in detecting financial statement fraud

S/N	Items(n=384)	SA	A	D	SD	Mean	Std.	Remark
8	Highly interpretable AI models improve the credibility of fraud detection results.	90	140	100	54	2.69	0.98	**Agreed**
9	Explainable AI (e.g., SHAP, LIME) enhances auditors' confidence in fraud detection.	85	150	95	54	2.68	0.97	**Agreed**
10	The interpretability of fraud detection models influences their adoption in financial audits.	100	135	90	59	2.72	0.99	**Agreed**
11	Auditors prefer models with clear explanations over black-box AI models in fraud detection.	95	145	95	49	2.74	0.98	**Agreed**
12	Interpretable AI models help in identifying the most critical fraud risk indicators.	110	130	90	54	2.64	0.97	**Agreed**
13	A balance between model accuracy and interpretability is necessary for effective fraud detection.	92	142	98	52	2.71	0.98	**Agreed**
14	Lack of interpretability in AI models creates challenges in financial fraud investigations.	98	138	93	55	2.53	0.98	**Agreed**
	Grand Mean					**2.67**	**0.98**	**Agreed**

Discussion of Findings

The findings from both research questions provide insight into the effectiveness of Natural Language Processing (NLP) and Model Interpretability in detecting financial statement fraud, drawing on respondents' views and existing studies, as well as interviews conducted.

Effect of Natural Language Processing in Detecting Financial Statement Fraud

With a grand mean of 2.66 in Table *, the findings' overall agreement shows that NLP is thought to be a useful technique for identifying financial statement fraud. In particular, machine learning-based NLP models (mean = 2.55) and sentiment analysis (mean = 2.73) are regarded as efficient fraud detection methods. This bolsters the results of previous research, including Smith et al, which discovered that by looking for odd linguistic patterns in financial accounts, NLP-driven sentiment analysis can successfully detect fraud indications. Additionally, the study of Jones and Zhang demonstrated the use of machine learning algorithms to financial data for fraud detection, emphasizing the usefulness of NLP models for identifying discrepancies in big datasets.

The findings of Brown and Green, who discovered that NLP technologies improve auditing processes by minimizing subjective judgment errors, thereby improving the accuracy of fraud detection, are consistent with the positive perception of NLP's capacity to lessen human bias (mean = 2.69) and its integration into audits (mean = 2.84). These results corroborate those of O'Neil, who observed that NLP tools increase the efficacy of financial audits by assisting auditors in concentrating on pertinent areas and removing human mistake.

Nonetheless, the disparity regarding NLP methods such as text mining (mean = 2.42) and the accuracy of NLP models in identifying discrepancies (mean = 2.82) indicates areas in need of development. These findings align with the views of Williams, who argued that while NLP techniques show promise, their application to text mining and identifying subtle discrepancies in financial statements remains a challenge, particularly due to the complexities of financial jargon and varied reporting formats. Mr. David Martins, Data Scientist at PwC, stated that "NLP has been transformative in analyzing large volumes of financial text, but the techniques need to evolve to better handle unstructured financial data." This aligns with the disagreement in Research Question One regarding the limitations of NLP techniques like text mining and model reliability.

Effect of Model Interpretability in Detecting Financial Statement Fraud

With mean scores ranging from 2.53 to 2.74, Table 4.2's results show considerable agreement regarding the beneficial impact of model interpretability in fraud detection. The unanimity that interpretable AI models are essential for improving fraud detection is highlighted by the "Grand Mean" of 2.67. This bolsters the conclusions of Lee and Lee (2020), who highlighted how crucial transparency in AI models is to building auditor trust and facilitating better decision-making. Furthermore, Kim found that explainable models like SHAP and LIME boost users' confidence in the AI's results, increasing their likelihood of being accepted in financial audits. This finding is consistent with the idea that interpretable models enhance fraud detection credibility and auditor confidence. Additionally, respondents concurred that interpretable models are beneficial.

In keeping with research by Jones, who discovered that explainable AI models make it easier for auditors to spot patterns that might point to fraudulent activity, particularly when contrasted with "black-box" models that lack transparency, respondents also concurred that interpretable models aid in identifying crucial fraud risk indicators. This is a crucial topic since, according to Sullivan et al, using interpretable models has been proposed as a means of resolving difficulties in comprehending AI decision-making processes. But the results also show that fraud investigations can be hampered by a lack of interpretability. This is consistent with the findings of Patel, who discovered that certain AI models' "black-box" nature makes it difficult to comprehend how decisions are made, especially in intricate financial audits. Because auditors need precise explanations of AI results in order to make well-informed choices, this issue is crucial. "AI-based models, particularly those that are explainable, have greatly improved fraud detection in audits, as they make the auditing process more transparent and less reliant on subjective judgment," stressed Dr. Emily Johnson, Senior Auditor at Deloitte. This bolsters the broad consensus regarding the significance of interpretability in Research Question Two.

The results indicate that NLP and model interpretability are both acknowledged as essential instruments for identifying financial statement fraud, albeit certain NLP limits have been noted.

With some limits found in particular NLP techniques (such as text mining) and in the dependability of specific models, the results indicate that both NLP and model interpretability are acknowledged as essential tools in detecting financial statement fraud. The increased demand for accuracy and transparency in AI-based systems used in financial audits is reflected in the general support for NLP's involvement in fraud detection and the desire for interpretable models. The conclusions drawn from previous research and expert interviews show the promise of these technologies while also recognizing the issues that must be resolved to maximize their efficacy in identifying financial fraud.

4. Conclusion

This study focused on Natural Language Processing (NLP) methods and Model Interpretability frameworks to investigate how well Artificial Intelligence (AI) detects financial statement fraud in Port Harcourt Metropolis, Nigeria. Results showed that, especially when models are clear and interpretable, AI-driven fraud detection greatly improves audit credibility, risk identification, and decision-making. Concerns were expressed over the dependability of certain methods, such as text mining, even though stakeholders, such as internal auditors, risk managers, and financial analysts, recognized the advantages of NLP-based fraud detection. The study underlined how important it is to strike a balance between interpretability and model accuracy in order to promote adoption and trust among financial professionals.

Furthermore, the reliability and validity evaluations validated the study instrument's consistency, guaranteeing reliable results. Banks and regulatory agencies must invest in explainable AI models and give financial professionals ongoing training to improve their comprehension and use of these technologies, especially in light of the growing reliance on AI in financial fraud detection. In conclusion, artificial intelligence (AI), especially natural language processing (NLP) and interpretable models, has a lot of promise for identifying financial statement fraud. However, its success hinges on appropriate application, industry-wide adoption, and regulatory support.

5. Recommendations

Based on the findings from the research objectives, the following recommendations are proposed:

1. Mandate the Use of Interpretable AI Models in Fraud Detection: Regulatory bodies should establish guidelines requiring the adoption of explainable AI models in financial audits. This will enhance transparency, improve fraud detection credibility, and ensure that auditors can easily interpret AI-generated fraud risk assessments.
2. Enhance NLP Integration and Training for Fraud Detection: Audit firms and financial institutions should invest in advanced NLP training for auditors and fraud investigators. This will improve their ability to utilize NLP tools effectively, address challenges in text mining, and enhance fraud detection by leveraging AI-driven sentiment analysis and anomaly detection in financial reports.

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