European Journal of Accounting, Auditing and Finance Research, 14(4),22-56, 2026
Print ISSN: 2053-4086(Print),
Online ISSN: 2053-4094(Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development-UK

Artificial Intelligence Adoption and Detection of Fraudulent Financial Statement in The Nigerian Public Sector: Role of Organisational Culture

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doi: https://doi.org/10.37745/ejaafr.2013/vol14n42256 Published June 08 , 2026

Citation: Appah E., Nkak P., Eburunobi E.O., Aganaba D. (2026) Artificial Intelligence Adoption and Detection of Fraudulent Financial Statement in The Nigerian Public Sector: Role of Organisational Culture, *European Journal of Accounting, Auditing and Finance Research*, 14(4),22-56

Abstract: *This study investigated the association between organizational culture and the effectiveness of artificial intelligence (AI) tools in detecting financial statement fraud in the public sector, with a focus on the moderating role of organizational culture. The increasing complexity of the public sector financial system and the growing use of AI-based fraud detection tools necessitate an understanding of contextual factors that influence their effectiveness. The study is grounded in institutional theory and adopts a quantitative research design complemented by explanatory correlational analysis. A population of 820 participants from the Bayelsa State Ministry of Finance were involved in accounting and auditing functions across public sector institutions, while a sample of 380 participants was drawn using a stratified random sampling technique. Primary and secondary data were employed with a questionnaire as the major source of data collection based on a 5-point Likert scale. The questionnaire was tested using content and face validity, while reliability was determined by the Cronbach's Alpha coefficient. The responses from the administered questionnaire were tested using univariate, bivariate and multivariate analysis. The SEM analysis revealed a positive and significant association between MAL, NLP, DTA, DIM, and EXS on the detection of financial statement fraud in the public sector. The results further revealed that organizational culture positively and significantly moderates the relationship between AI adoption and the detection of financial statement fraud in the public sector. The study concludes that AI tools alone are insufficient for optimal fraud detection performance in the public sector. Instead, their effectiveness is maximized when supported by a strong and ethical organizational culture. The study recommends that public sector institutions should integrate cultural development strategies with AI adoption policies to strengthen fraud detection systems and improve financial accountability.*

Keywords: Organisational culture, Artificial intelligence, fraud detection, financial statement fraud detection, public sector.

INTRODUCTION

The perseverance of accounting fraud in the Nigerian public sector continues to undermine fiscal discipline, governance quality, and public trust, despite decades of reforms and anti-corruption initiatives. According to Chinda and Obiosa (2025), fraudulent practices have long overwhelmed the public sector in Nigeria, with the South-South region being particularly susceptible. The authors further argue that embezzlement of public funds, inflated contracts, ghost workers, and other forms of fraudulent activities have weakened the efficient provision of public goods and services and have damaged public trust in government institutions. Fraudulent practices such as embezzlement and misappropriation of public funds to financial misreporting have been identified as systemic challenges that weaken institutional effectiveness and economic development in Nigeria. Empirical evidence indicates that fraud remains deeply entrenched within public institutions, largely due to weak internal control systems, poor transparency mechanisms, and limited technological capacity for proactive detection (Chinda & Obiosa, 2025; Vutumu et al., 2024; Vutumu et al., 2025). This challenge is particularly salient in resource-rich but administratively constrained regions such as Bayelsa State, where governance inefficiencies and financial leakages are often amplified. Chinda and Obiosa (2025) maintain that fraudulent activities have become predominantly severe in the South South region, which encompasses the six states of Akwa Ibom, Bayelsa, Cross River, Delta, Edo, and Rivers. Therefore, addressing public sector fraudulent practices in Nigeria involves a multilayered method that consists of robust internal controls, enhanced transparency, and the strategic deployment of specialized tools and technologies (Fatokun, et al, 2025; Chinda & Obiosa, 2025).

Traditionally, fraud detection in the Nigerian public sector relies on manual auditing procedures and rule-based internal control systems. According to Shahana et al (2023), conventional fraud detection approaches in accounting have relied heavily on manual processes, audits, and rule-based systems. Adelakun et al (2024a) argue that traditional approaches, though introductory, have numerous restrictions that make them less effective in the current landscape of complex financial transactions and sophisticated fraud schemes. Orthodox auditing involves the scrutiny of financial records by auditors to guarantee accuracy and compliance with accounting standards (Hazar et al., 2021). Although audits are critical for detecting fraudulent practices, they are limited by their periodic nature and reliance on sampling. Audits often occur annually or quarterly, which means that fraudulent actions can go undetected for extended periods (Adelakun et al, 2024b, Cheng et al., 2023). Moreover, the manual nature of audits makes them time-consuming and susceptible to human error. Rule-based fraud detection systems operate on predefined rules and thresholds to identify suspicious activities (Gianini et l., 2020). These traditional approaches, although vital, are progressively insufficient in the face of current fraud challenges (Ojone et al, 2024; Onogholo et al, 2025; Aliyu & Iheonkhan, 2025; Omorogbe et al, 2025). The growing volume and complexity of financial transactions, the speed at which transactions occur, and the sophistication of fraud techniques necessitate more advanced, adaptive, and proactive fraud detection solutions (Appah, 2025a; Appah, 2025b, Shoetan et al., 2024). Nevertheless, these approaches are gradually inadequate in solving the scale, sophistication, and real-time nature of modern accounting fraud. The emergence of Artificial Intelligence (AI) has presented a paradigm shift in accounting and auditing practices, offering innovative capabilities such as anomaly detection, predictive analytics, and automated data processing. According to Hasan (2021), artificial Intelligence (AI) has emerged as a transformative technology with the potential to revolutionize fraud detection in accounting. AI fraud detection systems offer real-time checking, prognostic analytics, pattern recognition, and machine learning competencies that permit organisations to recognize and avert fraudulent transactions before they occur. These systems can study from historical fraud forms and adjust to new threats vigorously, making them a superior alternative to conventional tools (Peña & Ortega-Castro, 2024; Jaeni & Astuti, 2024). AI can detect and prevent fraudulent practices by learning from past patterns to identify infrequent financial activities with superior accuracy, thus permitting instant detection of doubtful behaviour (Alaba et al, 2025). AI analyzes financial activity forms with greater speed and accuracy to detect doubtful forms that conventional approach cannot detect or prevent (Mediana & Sandari, 2024; Hassan, et al., 2023). AI's ability to process and analyze large-scale financial data offers a better benefit in recognizing doubtful forms. AI-driven fraud detection systems utilise advanced machine learning (ML) techniques involving supervised, unsupervised, and hybrid learning models to detect anomalies and fraudulent activities in organisational transactions (Islam & Rahman, 2025; Mallesha & Hymavathi, 2024; Baltgailis et al., 2024; Adeyelu et al, 2024).

Internationally and within Nigeria, AI is speedily becoming a dominant approach for fraud detection. Current indicates that approximately 87.5% of Nigerian fintech firms adopt AI largely for fraud detection, showing the increasing acknowledgement of its efficiency in risk management and financial investigation (Oke, 2026). Similarly, studies (such as Reddy et al., 2024, Aftabi et al., 2023, Tan et al., 2023, Nguyen et al., 2023, Elhassan et al., 2022, Shabbir et al., 2022, Bao et al., 2022, Psychoula et al., 2021, West, 2021, Craja et al., 2020) have shown that AI and machine learning significantly enhance the resilience and adaptability of fraud detection systems, enabling organizations to respond to evolving fraud schemes more efficiently than traditional methods. Within the public sector context, emerging research in Nigeria indicates that AI integration can substantially improve fraud prevention and detection outcomes by leveraging data-driven insights and real-time monitoring capabilities (Adebayo et al, 2023, Chinda & Obiosa, 2025, Okoye, 2024, Agba et al, 2023). Despite these potentials, the adoption of AI in the Nigerian public sector remains fragmented, slow, and uneven. Several structural and institutional barriers constrain its effective implementation, including high costs of deployment, inadequate technological infrastructure, lack of skilled personnel, and regulatory uncertainties (Adebayo et al, 2023, Chinda & Obiosa, 2025, Okoye, 2024, Agba et al, 2023, Omotosho et al, 2021, Adegboyega & Oladele, 2020). Consequently, empirical studies reveal that AI adoption is significantly influenced by organizational readiness factors such as IT infrastructure, staff competency, and perceived effectiveness of the technology. Furthermore, the bureaucratic nature of public sector institutions often limits flexibility, innovation, and responsiveness to technological change, thereby hindering AI diffusion (Alabi et al, 2025, Goyal, et al., 2025, Chinda & Obiosa, 2025, Okoye, 2024, Agba et al, 2023, Omotosho et al, 2021, Adegboyega & Oladele, 2020).

More critically, contemporary literature suggests that technological adoption alone is insufficient to guarantee improved fraud detection outcomes. The success of AI systems is conditional upon organizational setting, largely the interaction of organisational culture and management support.

Organizational culture refers to the shared system of values, beliefs, norms, and assumptions that guide how members of an organization think, behave, and make decisions. Recent literature defines organizational culture as the collective values, norms, goals, and expectations shared by members of an organization, which influence employee behaviour, commitment, and performance (Fernandes et al, 2023). Similarly, organizational culture can be understood as a set of shared beliefs and expectations that shape an organisation's identity, practices, and standards of behaviour (Chalmers et al, 2025). Bogale and Debela (2024) described organizational culture as the collection of underlying assumptions, values, and norms developed over time and transmitted to members as the correct way to perceive and respond to organizational challenges. Organizational culture plays a critical role in shaping how AI is adopted and employed in fraud detection processes. A strong ethical culture promotes transparency, accountability, and openness, which enhances the effectiveness of AI driven systems in identifying accounting fraud. Organizational culture influences the acceptance and implementation of AI systems. Ethical culture directly affects data integrity, which is essential for AI systems. Organizational culture determines the effectiveness of internal control systems, which work alongside AI technologies. A culture that emphasizes strong governance and compliance enhances AI's ability to detect fraudulent accounting practices. Studies have shown that combining AI with strong internal control systems significantly improves fraud detection rates (Vutumu et al, 2024; Vutumu et al, 2025). In the Nigerian public sector, where fraud and corruption remain significant concerns, integrating AI with a strong organizational culture can enhance accountability and service delivery. AI technologies can detect patterns of fraudulent activities, but their success depends largely on the institutional culture supporting their deployment.

In the specific context of Bayelsa State, there is a notable paucity of empirical research examining how these moderating variables influence AI-driven fraud detection in public sector accounting. While existing studies have largely focused on the banking and private sectors, there is limited understanding of how AI can be effectively deployed within government institutions characterized by unique administrative, cultural, and political dynamics. This gap underscores the need for a context-specific investigation that integrates technological innovation with organizational behaviour. Therefore, this study seeks to advance the literature by examining the moderating role of organisational culture and management support on the relationship between AI adoption and the detection of accounting fraud in the Nigerian public sector, with a specific focus on Bayelsa State. By doing so, the study contributes to a more nuanced understanding of how internal organizational factors shape the effectiveness of emerging technologies in combating financial misconduct and strengthening public sector accountability. This study is justified to by the persistent incidence of accounting fraud in the Nigerian public sector, which continues to undermine transparency, accountability, and effective resource utilization. Despite the establishment of internal control systems and anti-corruption agencies, fraudulent practices such as misappropriation of public funds and financial misreporting remain prevalent (Vutumu et al., 2025). Second, the study is justified on theoretical grounds, as it contributes to the integration of technological and organizational perspectives in understanding fraud detection. Third, the study addresses a significant empirical gap in literature. Most prior research on AI and fraud detection in Nigeria has focused on the banking and private sectors, with limited attention to the public sector where the problem of fraud is more pervasive and complex (Alaba et al., 2025). Fourth, the study is justified by its methodological contribution. Unlike many previous studies that rely on descriptive or simplistic analytical techniques, this research adopts a more robust analytical approach capable of examining complex relationships involving moderation effects. Finally, the study is justified by its societal relevance. By enhancing fraud detection mechanisms in the public sector, the study contributes to improved governance, efficient utilization of public resources, and increased public trust in government institutions. In a developing economy like Nigeria, where public funds are critical for infrastructure development and social services, reducing fraud has far-reaching implications for economic growth and social welfare. The main objective of this study is to investigate the moderating effects of organisational culture on the adoption of artificial intelligence and the detection of accounting fraud in the public sector of Bayelsa State, Nigeria. The following specific objectives were analysed in this study:

1. To investigate the effect of machine learning on the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria.
2. To assess the effect of natural language processing on the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria.
3. To determine whether data analytics on the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria.
4. To investigate the effect of data mining on the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria.
5. To evaluate the effect of expert systems on the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria.
6. To evaluate whether organisational culture moderates the relationship between the adoption of artificial intelligence and the detection of accounting fraud in the public sector of Bayelsa State, Nigeria.

The following research questions were analysed in this study:

1. What is the relationship between machine learning and the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria?
2. How does natural language processing affect the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria?
3. What is the relationship between data analytics and the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria?
4. How does data mining affect the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria?
5. How does an expert system affect the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria?
6. Does organisational culture moderate the relationship between the adoption of artificial intelligence and the detection of accounting fraud in the public sector of Bayelsa State, Nigeria?

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The study tested the following research hypotheses:

Ho_1: Machine learning has no significant effect on the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria.

Ho_2: Natural language processing has no significant effect on the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria.

Ho_3: Data analytics has no significant effect on the detection of financial statement fraud in the public sector of Bayelsa State, Nigeria.

Ho_4: There is no significant relationship between data mining and financial statement fraud in the public sector of Bayelsa State, Nigeria.

Ho_5: There is no significant relationship between expert systems and financial statement fraud in the public sector of Bayelsa State, Nigeria.

Ho_6: Organisational culture does not significantly moderate the relationship between the adoption of artificial intelligence and the detection of accounting fraud in the public sector of Bayelsa State, Nigeria.

Conceptual Review

Conceptual Framework

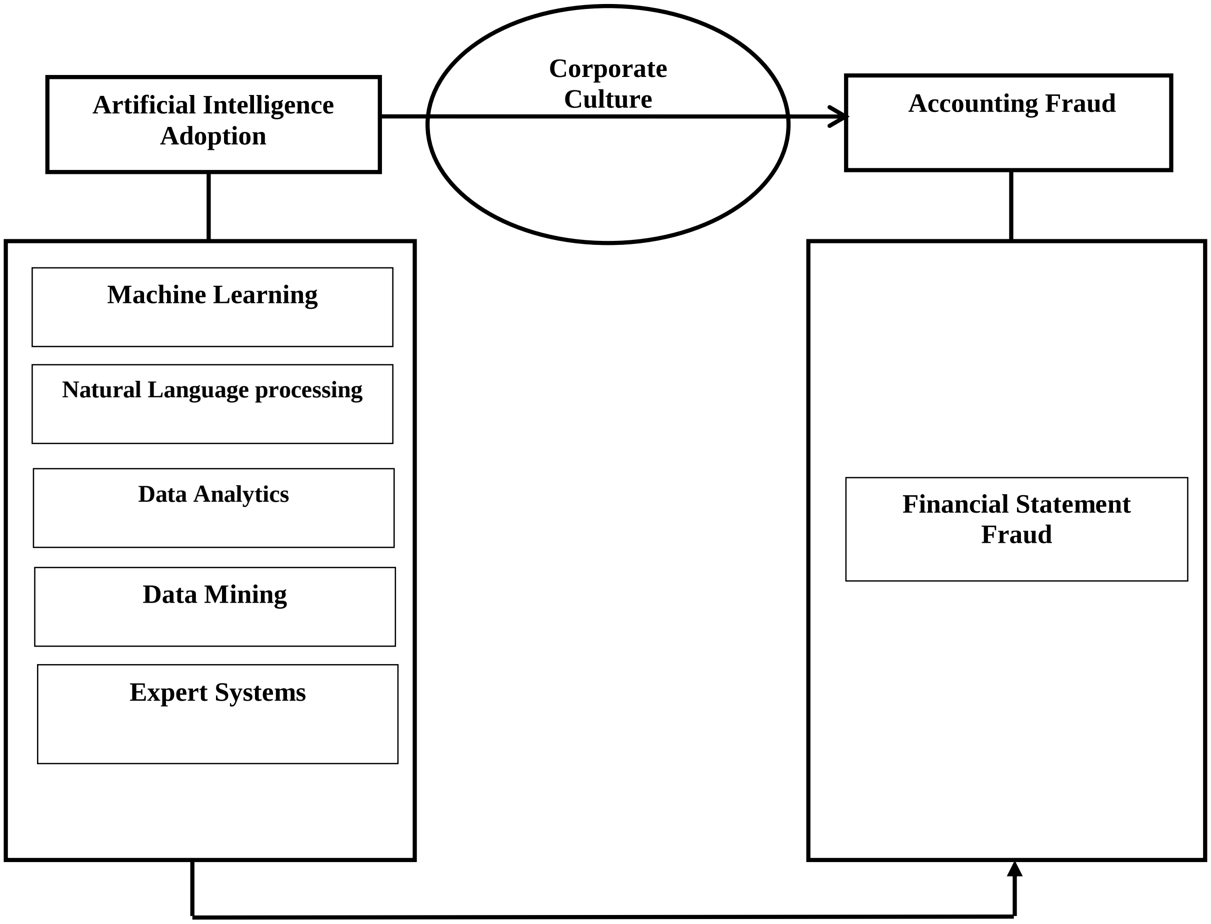

Figure 1: Conceptual Framework Authors' Creation

Concept of Artificial Intelligence: Artificial Intelligence (AI) denotes to the simulation of human intelligence processes by machines, particularly computer systems, to perform tasks such as learning, reasoning, problem-solving, and decision-making. In the context of accounting, AI covers technologies such as machine learning, natural language processing, and data mining, which allows computerized analysis of huge volumes of accounting transactions (Ojone et al, 2024, Onogholo et al, 2025, Aliyu & Iheonkhan, 2025, Omorogbe et al, 2025, Aftabi et al., 2023, Tan et al., 2023, Nguyen et al., 2023, Elhassan et al., 2022, Shabbir et al., 2022, Bao et al., 2022). AI covers a range of technologies, including machine learning (ML), natural language processing (NLP), data analytics, expert systems and data mining, that permit computerised systems to learn from data, identify patterns, and make decisions with minimal human intervention. ML algorithms can analyze vast amounts of financial data to detect patterns and anomalies that may indicate fraud (Adelakun et al, 2024a). AI mimics human cognitive processes using machines, particularly computer systems. It is often referred to as machine intelligence, AI is increasingly being adopted in the accounting world due to its role in managing vast databases of the world's wealth and facilitating information transactions across networks (Lukianenko & Simakhova, 2023). The implementation of AI in the industry offers numerous benefits, improving areas such as accounting, sales, contracts and cybersecurity. In addition, banks are increasingly partnering with financial technology (FinTech) companies to use AI to provide enhanced banking solutions during the production process (Baltgailis, et al., 2024). AI can detect and prevent fraud by learning from past patterns to identify unusual transactions with greater accuracy, thereby allowing for swift detection of suspicious behaviour. AI analyzes transaction patterns with high speed and accuracy to detect suspicious patterns that traditional systems cannot detect or prevent (Mediana & Sandari, 2024; Hassan, et al., 2023). AI’s ability to process and analyze large-scale data provides a good advantage in identifying suspicious patterns. AI-driven fraud detection systems utilize advanced machine learning (ML) techniques involving supervised, unsupervised, and hybrid learning models, to detect anomalies and fraudulent activities in banking transactions (Islam & Rahman, 2025; Baltgailis, et al., 2024). The use of artificial intelligence (AI) in enhancing the accuracy and efficiency of banking operations has gained a lot of traction for improving fraud detection rates, reducing false positives, and enhancing the overall security posture of financial institutions (Goyal, et al., 2025; Al Faisal, et al., 2024; Anzor, et al., 2024). The integration of AI into fraud detection offers numerous benefits. AI algorithms can process and analyze large volumes of data more accurately and efficiently than human auditors. They can identify subtle patterns and correlations that may be missed by traditional methods. AI systems can monitor transactions in real time, enabling the immediate identification and investigation of suspicious activities (Shabbir et al., 2022). This proactive approach helps to prevent fraud before significant losses occur. Unlike rule-based systems, AI algorithms can adapt to evolving fraud techniques. They continuously learn from new data and improve their detection capabilities over time. AI's ability to analyze data holistically reduces the occurrence of false positives (legitimate transactions flagged as fraud) and false negatives (fraudulent transactions that go undetected) (Bao et al., 2022).

Concept of Financial Statement Fraud Detection: Financial statement fraud refers to the intentional misappropriation or omission of financial information in an organisation’s financial reports to deceive users such as investors, creditors, regulators, or the public. According to Association of Certified Fraud Examiners (ACFE), financial statement fraud involves the deliberate manipulation of financial records to present a misleading picture of a firm’s financial health (ACFE, 2022). Similarly, American Institute of Certified Public Accountants (AICPA) defines it as an intentional act that results in materially misleading financial statements, often through falsification, alteration, or omission of accounting records (AICPA, 2019). AI has significantly improved the detection of financial statement fraud by providing advanced analytical tools capable of identifying hidden patterns and anomalies (Khurana et al., 2023; Shabbir et al., 2022). However, it should not replace human judgment but rather complement auditors’ expertise (Rangineni & Marupaka, 2023). A combination of AI technology, professional skepticism, and strong internal controls offers the most effective approach to combating financial statement fraud (Ijiga et al., 2024; Khurana et al., 2023).

Artificial Intelligence and Detection of Accounting Fraud: Accounting fraud detection refers to the processes and structures employed to identify, prevent, and respond to fraudulent financial activities within an organization. These activities may include financial misstatements, asset misappropriation, and corruption-related practices such as embezzlement and contract inflation. Traditionally, fraud detection has relied on manual auditing procedures, internal controls, and forensic accounting techniques. However, these methods are increasingly inadequate in detecting complex and evolving fraud schemes, particularly in environments characterized by large datasets and sophisticated financial transactions (Vutumu et al., 2025). Machine learning (ML) is a subset of artificial intelligence (AI) that focuses on building systems that can learn from and make decisions based on data (Blasch e al., 2021). In the context of fraud detection in accounting, ML techniques offer powerful tools for identifying and mitigating fraudulent activities. ML can be broadly categorized into supervised and unsupervised learning, each with distinct methodologies and applications. In fraud detection, supervised learning algorithms are trained using historical transaction data labeled as fraudulent or legitimate. The model learns patterns and characteristics associated with fraudulent transactions and can apply this knowledge to new, unseen data to predict the likelihood of fraud (Wang et al., 2021; Wahid & Hassini, 2024). Natural Language Processing (NLP) is a branch of AI that focuses on the interaction between computers and human language. It involves the ability of a computer to understand, interpret, and generate human language in a way that is valuable. NLP encompasses a variety of techniques, including text analysis, sentiment analysis, machine translation, and speech recognition (Khurana et al., 2023). NLP capabilities comprise extracting information and insights from textual data, determining the sentiment or emotional tone behind a series of words, identifying and classifying key entities (such as names, dates, and locations) within a text, creating human-like text based on input data, and translating text from one language to another. In fraud detection, NLP can be employed to analyze large volumes of textual data, such as emails, contracts, financial statements, and audit reports. By extracting and interpreting the information within these texts, NLP can uncover hidden relationships and detect suspicious activities (Adelakun et al, 2024a). Data mining is the process of discovering patterns, correlations, and anomalies within large datasets to predict outcomes (Gupta and Chandra, 2020). It involves various techniques, including classification, regression, clustering, association rule learning, and anomaly detection. Classification technique involves assigning items in a dataset to predefined categories or classes. AI-driven fraud detection systems leverage advanced algorithms and machine learning techniques to identify and prevent fraudulent activities more effectively than traditional methods (Ijiga et al., 2024). AI algorithms can analyze vast amounts of transaction data and learn complex patterns associated with fraud, leading to more accurate detection. Machine learning algorithms, such as supervised and unsupervised learning, are particularly effective in improving accuracy. AI-driven fraud detection systems significantly enhance the efficiency and speed of detection processes compared to manual or rule-based methods (Zanke, 2023). AI-driven fraud detection systems excel in analyzing large volumes of data, including structured and unstructured data from various sources such as transaction records, emails, social media, and sensor data (Umair, 2023). Adelakun et al (2024a) maintain that one of the significant benefits of AI-driven fraud detection is its ability to enable proactive fraud prevention through predictive analytics. By analyzing historical transaction data and identifying patterns indicative of fraudulent behavior, AI algorithms can anticipate and prevent future fraud incidents before they occur (Rangineni & Marupaka, 2023). AI-driven fraud detection offers a multitude of benefits to organizations across various industries, including increased accuracy, enhanced efficiency, large-scale data analysis capabilities, reduction of false positives and negatives, and proactive fraud prevention through predictive analytics (Jan et al., 2023).

Concept of Corporate Culture: Organizational culture refers to the shared system of values, beliefs, norms, and assumptions that guide how members of an organization think, behave, and make decisions. Recent literature defines organizational culture as the collective values, norms, goals, and expectations shared by members of an organization, which influence employee behaviour, commitment, and performance (Fernandes et al, 2023). Similarly, organizational culture can be understood as a set of shared beliefs and expectations that shape an organisation's identity, practices, and standards of behaviour (Chalmers et al, 2025). Bogale and Debela (2024) described organizational culture as the collection of underlying assumptions, values, and norms developed over time and transmitted to members as the correct way to perceive and respond to organizational challenges. Organizational culture plays a critical role in shaping how AI is adopted and employed in fraud detection processes. A strong ethical culture promotes transparency, accountability, and openness, which enhances the effectiveness of AI driven systems in identifying accounting fraud. Organizational culture influences the acceptance and implementation of AI systems. Ethical culture directly affects data integrity, which is essential for AI systems. Organizational culture determines the effectiveness of internal control systems, which work alongside AI technologies. A culture that emphasizes strong governance and compliance enhances AI's ability to detect fraudulent accounting practices. Studies have shown that combining AI with strong internal control systems significantly improves fraud detection rates (Vutumu et al, 2024; Vutumu et al, 2025). In the Nigerian public sector, where fraud and corruption remain significant concerns, integrating AI with a strong organizational culture can enhance accountability and service delivery. AI technologies can detect patterns of fraudulent activities, but their success depends largely on the institutional culture supporting their deployment.

Theoretical Review

Theoretically, this study is anchored in Institutional Theory (IT). This theory began as a crucial theme in the study of organizations, specifically in the 1940s, with the original creation by Selznick (1949). Selznick presented the view that organizations are not simply technical systems, but also social systems entirely guided by recognized norms and values. This pioneering work was trailed by contributions from Meyer and Rowan (1977), who observed that organizations adopt formal structures not only for efficiency but also to meet societal expectations, a phenomenon they described as 'rational myths.' They argued that organizational formality often serves to ensure legitimacy rather than optimise performance. This theory provides a robust theoretical perspective for understanding the adoption and effectiveness of AI in accounting fraud detection by situating technological innovation within broader systems of social expectations, regulatory frameworks, and legitimacy-seeking behaviour Ioakeimidou et al, (2023). The theory posits that organisational practices are not driven solely by efficiency considerations but are significantly shaped by regulative, normative, and cognitive pressures that define acceptable structures and behaviours within a given field. In the context of AI-enabled fraud detection, this implies that the deployment and utilisation of AI systems are deeply embedded in institutional environments that influence both their adoption and their operational outcomes (Goyal, et al., 2025; Al Faisal, et al., 2024;

Anzor, et al., 2024). The strength of IT lies in its explanatory depth and interdisciplinary relevance. A central merit of IT is its ability to explain organizational homogeinity through isomorphism. Another more recent strength is its focus on legitimacy as a driver of organizational behaviour. The theory also offers broad interdisciplinary applicability. Additionally, the theory is effective in explaining organizational persistence and path dependence. Despite these strengths, IT has been criticized for overemphasizing conformity and underestimating agency. Another criticism is its limited predictive power, conceptual ambiguity and fragmentation (Dimaggio & Power, 1983; Scott, 2014; Reis & Pinheiro, 2025). IT provides a robust framework for understanding how organizational structures, norms and governance mechanisms shape the adoption and effectiveness of AI in accounting systems. In the context of AI adoption, organizations implement AI-driven accounting systems not only for efficiency but also to achieve legitimacy within their institutional environments. Recent studies show that AI significantly improves fraud detection by analyzing large datasets, identifying anomalies, and enabling real-time monitoring of financial transactions (Adelakun et al, 2024a, 2024b). While AI enhances fraud detection through advanced analytics and automation, its effectiveness is contingent upon institutional determinants such as ethical culture and managerial commitment. These moderators determine whether AI systems are fully employed, trusted and embedded within organizational practices, ultimately shaping fraud detection in the public sector (Sastararuji et al, 2024).

The diffusion of innovation (DOI) theory was proposed by Everett Rogers in 1962 (Rogers, 1962) in his classic work Diffusion of Innovations. It seeks to explain how, why, and at what rate new ideas and technologies spread across societies and organizations. Rogers (2003) argues that diffusion is "the process by which an innovation is communicated through certain channels over time among the members of a social system" (p. 5). This implies that the adoption of an innovation is not just an individual decision based on utility but also a social process influenced by cultural and structural factors. According to Rogers, the adoption of an innovation follows a pattern, categorising individuals into five groups: innovators, early adopters, early majority, late majority, and laggards. Central to DOI theory are the five perceived attributes of innovation: related advantages, compatibility, complexity, trialability, and observability, which collectively shape adoption decisions and subsequent utilisation. In the context of AI and accounting fraud detection, relative advantage refers to the extent to which AI is perceived as superior to conventional fraud detection methods. Organisations that recognise AI's ability to enhance audit quality, detect complex fraud schemes, and provide real-time insights are more likely to adopt and effectively utilise these systems. Empirical evidence indicates that perceived performance gains are a primary driver of AI adoption in accounting environments (Sastararuji et al, 2024). Recent literature also underscores the interaction between DOI constructs and broader organisational and environmental factors. While DOI theory focuses on innovation attributes and diffusion processes, factors such as organisational culture, institutional pressures, and management support play critical roles in shaping adoption outcomes. For example, Yang et al. (2026) emphasise that challenges related to data quality, regulatory compliance, and ethical considerations significantly influence the adoption and effectiveness of AI systems. These factors interact with DOI attributes, reinforcing the need for an integrated theoretical approach. One major advantage of DOI theory is its ability to explain how and why innovations spread. The theory is highly versatile and has been applied in diverse fields, including accounting. The theory classifies individuals into adopter categories, which helps organisations tailor strategies for different groups. The theory highlights the relevance of social networks and communication channels in shaping adoption and provides a predictive model of adoption over time (Rudko et al, 2024; Reis & Pinheiro, 2025; Alabi et al, 2025). However, the theory has been criticized for its pro-innovation bias, which assumes that innovations should and will be adopted universally. DOI tends to underemphasize institutional, cultural and economic constraints that hinder adoption. The theory presents adoption as a relatively linear process, which may not reflect real-world complexity. The theory has been criticised for ignoring dynamics and social implications, and focuses primarily on adoption decisions, giving less attention to implementation, usage, and long-term sustainability of innovations Rudko et al, 2024; Reis & Pinheiro, 2025). The application of DOI provides a useful framework for understanding how AI enhances the detection of accounting fraud within organizations. The theory explains that the adoption of an innovation depends on users' perceptions of its relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). AI is considered an innovation that offers a significant relative advantage by improving the speed, accuracy, and efficiency of fraud detection. AI systems can process large datasets, identify irregular patterns, and detect anomalities indicative of fraudulent activities, thereby enhancing audit quality and reliability. DOI also suggests that the successful implementation of AI is shaped by organsational readiness and social system factors. As AI adoption increases within an organization, its observability encourages wider acceptance and continued use (Ojone et al, 2024, Onogholo et al, 2025, Aliyu & Iheonkhan, 2025, Omorogbe et al, 2025, Aftabi et al., 2023, Tan et al., 2023, Nguyen et al., 2023, Elhassan et al., 2022, Shabbir et al., 2022, Bao et al., 2022).

Empirical Review

Alaba et al (2025) investigated the adoption of AI-driven fraud detection systems in Nigerian banks, focusing on cost, compliance and staff competence. Using a quantitative survey design, the authors collected data from IT staff, fraud analysts, compliance officers, and managers across the five sampled banks. The study population comprised of 24 licensed banks and purposive sampling ensured respondents had relevant experience and data were analysed with SEM. Reliability and validity were confirmed using Cronbach's alpha and factor analysis. The study found that regulatory compliance and staff competency positively influence AI adoption, while cost had a mixed effect, hence discouraging smaller banks but seen as a strategic by larger banks. Overall, the study provides empirical evidence that the adoption of AI-driven fraud detection systems in Nigeria is largely determined by a combination of financial capability, regulatory pressures, and human capital development. The findings highlight that while cost remains a barrier, compliance requirements and employee competency serve as critical enablers for successful AI adoption.

Metha (2025) examined the application of AI-driven fraud detection using a risk scoring model to enhance security in the banking sector. The study adopted a quantitative research design, employing secondary data obtained from banking transaction records and fraud detection systems. The population comprised financial transaction datasets within banking institutions, from which a sample of labelled transaction data was selected for analysis. The methodology involved the development of a machine-learning-based risk scoring model, where algorithms such as classification models were trained to assign risk scores to transactions based on behavioural patterns and anomaly detection. The study found that the AI-driven risk scoring model significantly improves fraud detection by accurately identifying high-risk transactions in real-time and reducing false positives compared to traditional rule-based systems.

Chinda and Obiosa (2025) investigated the effect of AI in fraud prevention and detection within public sector institutions in South-South of Nigeria. The study adopted mixed-methods research design, combining both quantitative and qualitative approaches to provide a comprehensive analysis. The population comprised public sector employees, auditors, fraud investigators, and IT professionals across the six South-South states, from which a sample of knowledgeable respondents was selected, and a sample size of 300 respondents was determined using Krejcie and Morgan's table for sampling. Data was collected using structured questionnaires and interviews, while analysis involved both statistical techniques and descriptive evaluation. The findings revealed that AI systems of data analytics, machine learning, and natural language processing have significant positive effects on fraud prevention mechanisms, particularly in strengthening internal controls and auditing processes, and whistleblowing systems. Specifically, data analytics showed the strongest influence on internal control and audit, followed by machine learning and natural language processing, with all showing a statistically significant link. The findings showed that AI adoption enhances fraud detection efficiency and transparency in the public sector.

Hijriani et al (2025) explored the potential misuse of AI systems on facilitating banking fraud, focusing on emerging risks connected with advanced technologies. The study adopted a qualitative research design, drawing on case study analysis and expert insights from banking and cybersecurity experts. The population comprised stakeholders within the banking and financial technology ecosystem, while the sample included experts such as IT sepcialists, fraud analysts, and security experts selected purposively based on the knowledge of AI systems. Data was collected through interviews, document analysis, and reviews of reported fraud cases, and analysed using thematic analysis to identify patterns of AI misuse. Empirical evidence from the study indicated that while AI enhances fraud detection, it can also be exploited for fraudulent activities such as automated phishing, identity spoofing, deep-fake-based social engineering, and systems manipulation. The study revealed that weak regulatory frameworks, inadequate system monitoring, and limited technical expertise increase vulnerability to such misuse. The study concludes that although AI presents significant benefits to the banking sector security, its dual use nature requires strong governance frameworks, continuous monitoring, and improved cybersecurity capacity to mitigate emerging fraud risks.

Islam and Rahman (2025) conducted a comprehensive study on the application of AI in fraud detection within financial institutions, with emphasis on machine learning and anomaly detection techniques. The study adopted a quantitative, data driven research design, relying on secondary dataset to evaluate the effectiveness of AI models. The population comprised financial records from banking systems, from which a sample of labeled data was analysed. Methodologically, the authors implemented supervised and unsupervised machine learning models, including decision trees, random forests, and clustering algorithms, alongside deep learning and anomaly detection techniques to identify fraudulent patterns. Model performance was assessed using evaluation metrics. The findings showed that AI-driven models significantly outperform traditional rule-based systems, demonstrating higher accuracy, faster processing speed, and improve adaptability to evolving fraud patterns. The study further showed that AI systems can detect complex and previously unseen fraud behaviours through real-time data analysis, thereby enhancing financial security.

Aljunaid et al (2025) investigated the application of AI in enhancing fraud detection and prevention in the banking sector. The study adopted a quantitative research design, employing secondary data derived from financial transaction records and fraud detection systems. The population comprised banking transaction datasets, from which a large sample of labelled transactional data was selected for analysis. The researchers employed machine learning techniques, including classification algorithms, to develop predictive fraud detection models. Data analysis involved evaluating model performance using statistical metrics such as accuracy, precision, recall, and F1-score, alongside validation techniques to ensure model reliability. The findings revealed that AI-based models significantly improve fraud detection accuracy and speed. The study further showed that continuous model training and high-quality data are critical to maintaining performance, while integration with existing banking systems enhances real-time decision making. Hence, the research provides strong evidence that AI-driven techniques can substantially strengthen fraud detection and prevention mechanisms in modern banking systems.

Mediana and Sandari (2024) explored how AI is implemented in internal audit functions for fraud detection and prevention in the banking sector. The study adopted a qualitative research design using interviews and questionnaires administered to bank employees involved in audit and fraud management to gather in-depth insights into current practices and perceptions of AI use. The study sample included employees from multiple roles within the banking sector who had direct experience with internal audit systems and AI applications, enabling the authors to obtain rich, descriptive data about real-world implementation. The authors analysed responses thematically to understand how AI adoption was employed. Empirical evidence from the study AI enhances audit efficiency by enabling real-time analysis of large data sets, reducing human error, and increasing customer trust, but the competency gap in auditor training and data management issues remains a key challenge to full implementation. The findings underscore that while AI has significant potential to strengthen fraud detection and internal audit effectiveness in banks, organisational readiness and continuous capacity building are critical for realising its merits.

Anzor et al (2024) examined the effect of AI on fraud detection in deposit money banks in Southeast of Nigeria, with emphasis on technologies such as computer vision and robotic process automation. The study adopted a quantitative research design, using a survey method to collect primary data from bank employees involved in fraud monitoring and IT operations. The population comprised staff of deposit banks in the Southeast of Nigeria, from which a sample of respondents was selected to provide evidence on AI-based fraud detection systems. Data was analysed using inferential statistical techniques, particularly the Z-test, to determine the significance of AI tools on fraud detection performance. The empirical findings showed that AI technologies have a significant positive effect on fraud detection, particularly in monitoring care-related fraud and detecting insider threats. Specifically, the study found that robotic process automation significantly improved monitoring, with statistical results indicating strong significance (Z value indicating $p < 0.05$). The study concludes that integrating AI into banking systems enhances fraud detection efficiency, accuracy and response time.

METHODOLOGY

This study adopts a quantitative research design complemented by explanatory correlational analysis. Quantitative methods are appropriate because the study seeks to measure the relationships between AI adoption, accounting fraud detection, and the moderating roles of organisational culture and management support in a structured and replicable manner. The study is cross-sectional, collecting data at a single point in time from relevant public sector institutions in Bayelsa State. A cross-sectional design is suitable for examining current adoption levels of AI, organisational culture, and management support, and for assessing their relationships with accounting fraud detection effectiveness (Appah, 2020; Ezie, 2022). The research also incorporates a moderation framework to test how organisational culture and management support influence the strength of the relationship between AI adoption and fraud detection outcomes. This approach aligns with best practices in organisational and information systems research (Ezie & Ezie, 2025a). The target population comprises accounting and auditing staff in Nigerian public sector institutions in Bayelsa State, including state ministries, parastatals, and local government offices involved in financial management. These participants are directly involved in implementing accounting systems, internal controls, and audit procedures, making them suitable informants for AI adoption and fraud detection practices (Adelakun et al, 2024; Alaba et al, 2025). Based on records from the Bayelsa State Ministry of Finance, there are 820 employees involved in accounting and auditing functions across public sector institutions. A sample of 380 participants was drawn using a stratified random sampling technique. Stratification is based on organisational type (ministries, parastatals, local government offices) to ensure proportional representation of diverse public sector units. The sample size is justified using the Krejcie and Morgan table and aligns with quantitative SEM studies suggesting minimum sample sizes of 380 for robust moderation analysis (Hair et al., 2021). Stratification enhances representativeness and reduces sampling bias. Data was collected using a structured questionnaire, divided into three sections of demographics – Age, gender, position, years of experience, adoption of AI – Measured using items adapted from Alaba et al. (2025) and Lawal & Adeyeye (2025), covering AI use for auditing, anomaly detection, and automated reporting, accounting fraud detection – Measured with scales adapted from Adelakun et al. (2024a), including perceived improvements in detection effectiveness, anomaly identification, and reporting accuracy. Moderator variable of organisational culture – Organisational culture items adapted from Chalmers et al (2025). Bogale and Debela (2024) capturing innovation, accountability, and change readiness. All items are measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The questionnaire used content and face validity checks by experts in accounting, information systems, and organisational behaviour. A pilot test with 30 respondents was used to assess reliability, using Cronbach's alpha, with a threshold of 0.70 considered acceptable (Appah, 2020; Ezie & Ezie, 2025a). Data collection followed the permission and access – that is, obtaining approval from the Bayelsa State Ministry of Finance and relevant institutional heads. Questionnaire Administration – Distribute printed and electronic questionnaires to sampled employees and address ethical considerations to ensure voluntary participation, informed consent, confidentiality, and anonymity of responses. Participants will be informed that the study is for academic purposes. The study employed quantitative statistical analysis using SPSS and SmartPLS for descriptive statistics such as means, standard deviations, and frequency distributions to summarise respondents' characteristics and variable scores. Also, reliability Analysis using Cronbach's alpha and composite reliability to ensure instrument consistency. Correlation analysis using Pearson correlation to assess preliminary relationships between AI adoption, fraud detection, and moderating variables. The study further used regression analysis and moderation testing using hierarchical regression will test the moderating effects of organisational culture and management support. Structural Equation Modelling (SEM) – Using SmartPLS, SEM was applied to test the theoretical framework and assess direct, indirect, and moderating effects simultaneously, providing robust model fit indices (Ezie & Ezie, 2025b). The multiple regression was guided by a linear model below:

$$FSF = \beta_0 + \beta_1 MAL + \beta_2 NLP + \beta_3 DTA + \beta_4 DTM + \beta_5 EXS + \varepsilon \quad \text{.......................................}(1)$$

$$FSF = \beta_0 + \beta_1 MAL + \beta_2 NLP + \beta_3 DTA +\# \beta_4 DTM + \beta_5 EXS + \beta_6 COC + \beta_7 (MAL * MAS) + \beta_8 (NLP * COC) + \beta_9 (DTA * COC) + \beta_{10} (DTM * COC) + \beta_{11} (EXS * COC) + \varepsilon \quad \text{.................} (2)$$

Where:

MAL = Machine Learning, NLP = Natural Language Processing, DTA = Data Analytics, DTM = Data Mining, EXS = Expert System, COC = Corporate Culture, FSF = Financial Statement Fraud. $\beta_0 - \beta_5$ represent the regression coefficient; $\beta_6 - \beta_{11}$ represent the moderating effects coefficients, while ϵ represents the error term. According to Appah (2020), the interpretation of correlation (r) parameters is 0.8 – 1.0 = very strong relationship, 0.6 – 0.79 = strong relationship, 0.4 – 0.59 = moderate relationship, 0.2 – 0.39 = weak relationship; and 0.0 – 0.19 = very weak or no relationship. The study utilised a 5% level of significance; hence we conclude that the coefficient is significantly different from zero at the 5% level if the p-values is less than or equal to 0.05. If it is greater than 0.05 then we cannot reject the null hypothesis that the coefficient is zero at our 5% significance level.

Data Presentation and Analysis

The primary data was collected from respondents using the questionnaire. The questionnaire was distributed and later retrieved by the respondents. The primary data collected was then subjected to analysis. From the sample, 380 copies of the questionnaire were distributed.

Table 1 Questionnaire Distribution

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Number Retrieved	322	84.7	84.7	84.7
	Number not retrieved	35	9.2	9.2	93.9
	Number not properly filed	23	6.1	6.1	100.0
	Total	380	100.0	100.0	

Table 1 shows the distribution and collection of questionnaires sent to the respondents. It was shown that 380 questionnaires were distributed to the respondents, representing 100%. 322

European Journal of Accounting, Auditing and Finance Research, 14(4),22-56, 2026
Print ISSN: 2053-4086(Print),
Online ISSN: 2053-4094(Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development-UK

questionnaires representing 84.7% were correctly filled and successfully retrieved from the respondents; however, 35 questionnaires representing 9.2% were not retrieved, and 23 questionnaires representing 6.1% were not properly filed. Consequently, only 322 questionnaires representing 84.7% will be used for data analysis.

Table 2 Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	256	67.4	67.4	67.4
	Female	124	32.6	32.6	100.0
	Total	380	100.0	100.0	

Table 2 shows the gender of respondents in the sample of the study. 67.4% which translates to two hundred and fifty-six (256) respondents, are male, while 32.6%, which translates to one hundred and twenty-four (124) respondents, are female. This implies that there is a diverse gender representation among the target respondents in the public sector of Bayelsa State, Nigeria.

Table 3 Age Range

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18 – 25 years	52	13.7	13.7	13.7
	26 – 35 years	75	19.7	19.7	33.4
	36 – 45 years	108	28.4	28.4	61.8
	46 – 55 years	122	32.1	32.1	93.9
	56 and above years	23	6.1	6.1	100.0
	Total	380	100.0	100.0	

Table 3 shows the age range of respondents. It was shown that 52 respondents representing 13.7% are between the age brackets of 18 – 25 years, 75 respondents representing 19.7% are between the age bracket of 26 – 35 years, 108 respondents representing 28.4% are between the age bracket of 36 – 45 years, 122 respondents representing 32.1% are between the age bracket of 46 – 55 years, 23 respondents representing 6.1% are between the age bracket of 56 and above years.

Table 4 Educational Qualification

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	OND/HND	45	11.8	11.8	11.8
	Bachelor's Degree	138	36.3	36.3	48.1
	Masters Degree	61	16.1	16.1	64.2
	Doctorate Degree	10	2.6	2.6	66.8
	Professional Certification	126	33.2	33.2	100.0
	Total	380	100.0	100.0	

Table 4 presents the educational qualifications of respondents. It was shown that 45 respondents representing 11.8% have OND/HND, 138 respondents representing 36.3% have bachelor's degrees, 61 respondents representing 16.1% have master's degrees, 10 respondents representing 2.6% have doctorate degrees, while 126 respondents have professional certification (ICAN or ANAN). This distribution offers insights into the educational backgrounds of the study sample

Table 5: Descriptive Statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
FSF	322	4.00	1.00	5.00	3.2152	.14171	1.42318	2.470
MAL	322	4.00	1.00	5.00	3.2634	.13450	1.43265	2.225
NLP	322	4.00	1.00	5.00	3.2365	.13061	1.32176	2.098
DTA	322	4.00	1.00	5.00	3.8531	.13116	1.53268	2.116
DIM	322	4.00	1.00	5.00	3.3287	.12541	1.43276	1.934
EXS	322	4.00	1.00	5.00	3.2654	.12946	1.32438	2.061
COC	322	4.00	1.00	5.00	2.6548	.14080	1.42387	2.438
Valid N (listwise)	322							
Source: Field Survey (2026)					**3.272442**		**1.41304**	

The results in Table 5 revealed the descriptive statistics of the Range, Minimum, Maximum Mean, Standard Deviation and Variance of responses on the moderating role of corporate culture on the artificial intelligence adoption and accounting fraud detection (financial statement fraud) in the Bayelsa State public sector of Nigeria, using five questionnaire items that were designed on a five-point Likert scale. Thus, all the variables' means are above the cut-off point of **2.5**. However, the grand mean and standard deviation responses on the questionnaire items are disclosed (M=**3.272442**; SD=**1.41304**), respectively.

Table 6: Descriptive Statistics of Machine Learning

S/N	Items	N	Min	Max	Mean	Std. D
1	Machine learning improves the accuracy of detecting financial statement fraud	322	1.00	5.00	3.539	1.294
2	Machine learning can identify fraud patterns that traditional auditing methods may miss	322	1.00	5.00	3.752	1.263
3	The use of machine learning enhances the reliability of financial reporting	322	1.00	5.00	3.427	1.215
4	Machine learning enables the early detection of fraudulent financial activities.	322	1.00	5.00	3.145	1.234
5	Machine learning speeds up the fraud detection process in financial statements	322	1.00	5.00	3.753	1.242
Valid N (listwise)		**322**			**3.482**	**1.272**

Source: Field Survey (2026)

The results in Table 6 show the descriptive statistics of the mean and standard deviation responses on the adoption of machine learning tool of AI questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items were labelled, and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on the adoption of machine learning tool of AI. Notwithstanding, all the items mean items above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.482; Std. D =1.272**), respectively.

Table 7: Descriptive Statistics of Natural Language Processing

S/N	Items	N	Min	Max	Mean	Std. D
1	NLP improves the detection of fraud in financial statements	322	1.00	5.00	3.709	1.315
2	NLP can identify misleading or deceptive language in financial disclosures	322	1.00	5.00	3.486	1.303
3	NLP helps detect inconsistencies in management reports and notes to accounts	322	1.00	5.00	3.522	1.300
4	NLP enhances the quality of fraud detection in financial reporting	322	1.00	5.00	3.717	1.227
5	NLP can analyse large volumes of financial data efficiently.	322	1.00	5.00	3.932	1.210
Valid N (listwise)		**322**			**3.673**	**1.258**

Source: Field Survey, 2026

The results in Table 7 indicate the descriptive statistics of the mean and standard deviation responses on the adoption of NLP tool of AI questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items were labelled, and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on the NLP tool of AI. Notwithstanding, all the items mean items above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.673; Std. D =1.258**), respectively.

Table 8: Descriptive Statistics of Data Analytics

S/N	Items	N	Min	Max	Mean	Std. D
1	DTA improves the detection of financial statement fraud in the public sector	332	1.00	5.00	3.609	1.293
2	DTA helps identify unusual patterns in financial data in the public sector	322	1.00	5.00	3.812	1.268
3	DTA enhances the accuracy of fraud detection in the public sector	322	1.00	5.00	3.609	1.365
4	DTA improves the identification of hidden financial irregularities in the public sector	322	1.00	5.00	3.581	1.273
5	DTA complements traditional auditing techniques in financial statement fraud in the public sector.	322	1.00	5.00	3.601	1.290
Valid N (listwise)		**322**			**3.642**	**1.298**

Source: Field Survey (2026)

The results in Table 8 reveal the descriptive statistics of the mean and standard deviation responses on the adoption of DTA tool of AI questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items were labelled, and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on DTA tool of AI. Notwithstanding, all the items mean items above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.673; Std. D =1.258**), respectively.

Table 9: Descriptive Statistics of Data Mining

S/N	Items	N	Min	Max	Mean	Std. D
1	DIM improves the detection of financial statement fraud in the public sector	322	1.00	5.00	3.709	1.315
2	DIM helps uncover hidden patterns in financial data in the public sector	322	1.00	5.00	3.486	1.303
3	DIM enhances the accuracy of financial statement fraud detection in the public sector.	322	1.00	5.00	3.522	1.300
4	DIM improves the detection of complex financial statement fraud schemes in the public sector.	322	1.00	5.00	3.717	1.227
5	DIM identifies links and trends that may indicate financial statement fraud in the public sector.	322	1.00	5.00	3.932	1.210
Valid N (listwise)		**322**			**3.753**	**1.228**

Source: Field Survey (2026)

The results in Table 9 represent the descriptive statistics of the mean and standard deviation responses on the DTM tool of AI questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items were labelled, and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on DTM tool of AI. Notwithstanding, all the items mean items above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.753; Std. D =1.228**), respectively.

Table 10: Descriptive Statistics of Expert Systems

S/N	Items	N	Min	Max	Mean	Std. D
1	EXS improves the detection of financial statement fraud in the public sector	322	1.00	5.00	2.709	1.315
2	EXS can replicate human expert judgment in fraud detection in public sector	322	1.00	5.00	2.486	1.303
3	EXS enhances the accuracy of detecting fraudulent financial reporting in the public sector.	322	1.00	5.00	2.522	1.300
4	EXS can identify irregularities in financial statement in the public sector	322	1.00	5.00	3.717	1.227
5	EXS enable consistent and reliable fraud detection decisions in the public sector.	322	1.00	5.00	3.932	1.210
Valid N (listwise)		**322**			**2.854**	**1.234**

Source: Field Survey (2026)

The results in Table 10 reveal the descriptive statistics of the mean and standard deviation responses on EXS tool of AI questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items were labelled, and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on the EXS tool of AI. Notwithstanding, all the items mean items above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =2.854; Std. D =1.234**), respectively.

Table 11: Descriptive Statistics of Corporate Culture

S/N	Items	N	Min	Max	Mean	Std. D
1	A strong COC enhances the effectiveness of AI in detecting financial statement fraud in the public sector	322	1.00	5.00	3.709	1.315
2	Ethical values improve the reliability of AI based financial statement fraud detection systems in the public sector.	322	1.00	5.00	3.486	1.303
3	COC influences how AI outputs are interpreted and used in the public sector.	322	1.00	5.00	3.522	1.300
4	COC supports the integration of AI in financial statement fraud detection in the public sector.	322	1.00	5.00	3.717	1.227
5	The combination of AI and strong COC improves financial statement fraud detection outcomes in the public sector.	322	1.00	5.00	3.932	1.210
Valid N (listwise)		**322**			**3.795**	**1.258**

Source: Field Survey (2026)

The results in Table 11 reveal the descriptive statistics of the mean and standard deviation responses on COC questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items were labelled, and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on COC. Notwithstanding, all the items mean items above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean = 3.795; Std. D =1.258**), respectively.

Table 12: Results of Correlation Matrix

		FSF	MAL	NLP	DTA	DIM	EXS
FSF	Pearson Correlation	1					
	Significant (2 tailed)	.000					
	N	322					
MAL	Pearson Correlation	.623**	1				
	Significant (2 tailed)	.000	.000				
	N	322	322				
NLP	Pearson Correlation	.673**	.646**	1			
	Significant (2 tailed)	.000	.000	.000			
	N	322	322	322			
DTA	Pearson Correlation	.658**	.726**	.726**	1		
	Significant (2 tailed)	.000	.000	.000	.000		
	N	322	322	322	322		
DIM	Pearson Correlation	.748**	.624**	.615**	.684**	1	
	Significant (2 tailed)	.000	.000	.000	.000	.000	
	N	322	322	322	322	322	
EXS	Pearson Correlation	.764**	.746**	.748**	.728**	.642**	1
	Significant (2 tailed)	.000	.000	.000	.000	.000	.000
	N	322	322	322	322	322	322

Source: Computed by Researcher's Via SPSS (2026)

Table 12 shows the Pearson Product Moment Correlation Coefficient (PPMC) analysis shows the relationship between AI tools and financial statement fraud detection in the public sector of Bayelsa State, Nigeria. The table shows a strong and positive relationship (r = 0.623, P = 0.00) between machine learning (MAL) of AI and detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, a strong and positive (r = 0.673, P = 0.000) between natural language processing (NLP) of AI and detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, a strong and positive (r = 0.658. P = 0.000) between data analytics (DTA) of AI and detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, a strong and positive (r = 0.748, P = 0.000) between data mining (DIM) of AI and detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, and a strong and positive (r = 0.764, P = 0.000) between expert system (EXS) of AI and detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria. Therefore, the findings therefore revealed a strong and positive relationship between the adoption of AI tools of MAL, NLP, DTA, DIM and EXS on the detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria.

Table 13: R-Square Adj.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Financial Statement Fraud	0.625	0.568	0.152	4.112	0.027

Source: Authors' Computation (2026)

The study investigated the relationship between AI adoption and financial statement fraud detection in the public sector of Bayelsa State, Nigeria, with acting as a moderating variable. The adjusted R^2 of 0.625 indicates that the model explains 62.5% of the variance in financial statement fraud detection in the public sector of Bayelsa State, Nigeria.

Table 14: AI Tools Adoption & Corporate Culture on Financial Statement Fraud

	Original Sample (O)	Sample Mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Remarks
MAL -> FSF	1.936	1.990	0.824	2.349	**0.024**	**H1 Supported**
NLP -> FSF	3.685	4.109	1.839	2.004	**0.048**	**H2 Supported**
DTA -> FSF	4.900	5.177	1.691	2.897	**0.004**	**H3 Supported**
DIM-> FSF	0.238	0.099	0.111	2.153	**0.038**	**H4 Supported**
EXS-> FSF	1.232	1.413	0.448	2.751	**0.005**	**H5 Supported**
COC -> FSF	2.195	2.043	0.812	2.703	**0.007**	**H6 Supported**
COC x MAL -> FSF	0.390	0.407	0.134	2.920	**0.003**	**H7 Supported**
COC x NLP-> FSF	1.323	1.491	0.620	2.135	**0.036**	**H8 Supported**
COC x DTA -> FSF	1.095	1.196	0.402	2.379	**0.012**	**H9 Supported**
COC x DIM -> FSF	1.014	1.041	0.500	2.028	**0.042**	**H10 Supported**
COC x EXS -> FSF	0.396	0.466	0.143	2.778	**0.006**	**H11 Supported**

Source: Authors' Computation (2026)

In Table 14 the first hypothesis (**H_1)**, which proposed that machine learning (MAL) positively and significantly affects the detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the result was significant (β = 1.936, t = 2.349, p = .024), leading to the support of **H_1**. For **H_2**, concerning natural language processing (NLP) positively and significantly affects the detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the result was significant (β = 3.685, t = 2.004, p = .048), thus **H_2** was supported. For **H_3**, which proposed that data analytics (DTA) positively and significantly affects the detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the result was significant (β =4.900, t = 2.897, p = .004), meaning **H_3** was supported. For **H_4**, relating to data mining (DIM) positively and significantly affects the detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the finding was significant (β = 0.238, t = 2.153, p = .038), leading to the support of **H_4. For H_5,** expert system (EXS) positively and significantly affects the detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria; the finding was significant (β = 1.232, t = 2.751, p = .005), thus **H_5** was supported.

The moderation analysis showed that **H_6**, which posited that corporate culture (COC) positively and significantly affects detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the finding was also significant (β = 2.195, t = 2.703, p = .007), thus **H_6** was supported. For **H_7**, concerning corporate culture (COC) positively and significantly moderates the relationship between machine learning (MAL) and detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the result was significant (β = 0.390, t = 2.920, p = .003), leading to the support of **H_7**. For **H_8,** concerning corporate culture (COC) positively and significantly moderates the relationship between natural language processing (NLP) and detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the finding was significant (β = 1.323, t = 2.135, p = .036), meaning **H_8** was supported. For **H_9**, about corporate culture (COC) positively and significantly moderates the relationship between data analytics (DTA) and detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the result was also significant (β = 1.095, t = 2.379, p = .012), leading to the support of **H_9**. For **H_{10}**, concerning corporate culture (COC) positively and significantly moderates the relationship between data mining (DIM) and detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the outcome was significant (β = 1.014, t = 2.028, p = .042), thus H10 was supported. Finally, for **H_{11}**, which proposed that corporate culture (COC) positively and significantly moderates the relationship between detection of financial statement fraud (FSF) in the public sector of Bayelsa State, Nigeria, the result was significant (β = 0.396, t = 2.778, p = .006), meaning that **H_{11}** was supported.

Print ISSN: 2053-4086(Print),
Online ISSN: 2053-4094(Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development-UK

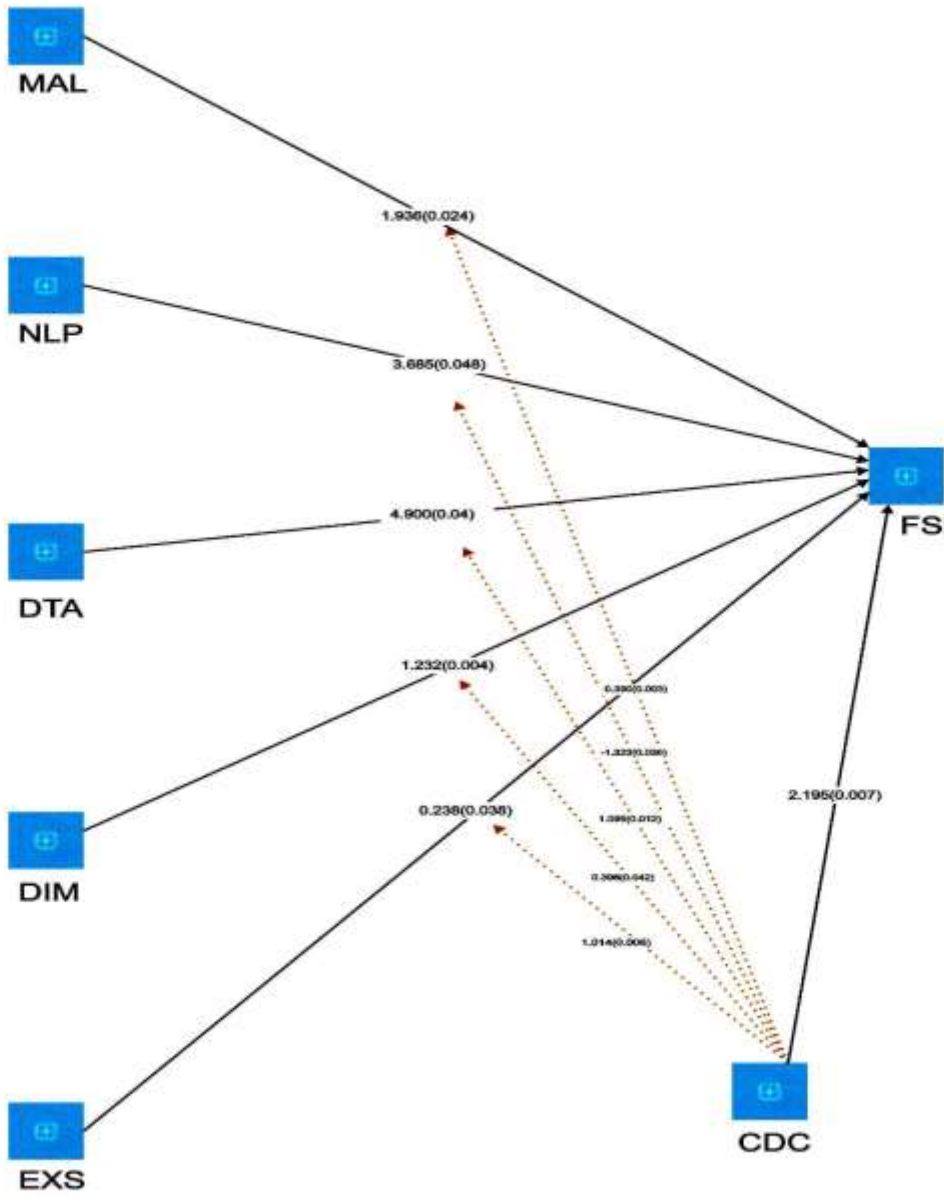

Figure 2: Process-Based Approach of Smart PLS

DISCUSSION OF FINDINGS

Machine Learning and Detection of Financial Statement Fraud: The findings revealed a significantly positive link between machine learning (AI) and the detection of financial statement fraud in the public sector. This suggests that implementing the MAL technique in AI can enhance the detection of financial statement fraud in the public sector. This aligns with the research conducted by Chinda and Obiosa (2025) on AI and public sector fraud detection and prevention. Their study revealed that machine learning significantly and positively influences the detection and prevention of public sector fraud. Similarly, the study is consistent with that of Omorogbe et al (2025), Aljunaid et al (2025), Reddy et al., (2024), that the adoption of AI technologies has the potential to significantly and positively enhance the effectiveness of fraud detection efforts by organisations. This shows that this technology can also contribute meaningfully to improving detection of financial statement fraud possibly through automated pattern recognition and the ability to process and analyze unstructured data such as text documents (Chen & Wong, 2023; Okoye, 2024). Njoku et al (2024) maintained that the application of machine learning algorithms and real-time fraud detection systems produced significant enhancements in organisation's fraud prevention proficiencies.

Natural Language Processing and Detection of Financial Statement Fraud: The results showed a positive and significant association between natural language processing (AI) and the detection of financial statement fraud in the public sector. This suggests that implementing the NAL technique in AI can enhance the detection of financial statement fraud in the public sector. This is consistent with the study by Chinda and Obiosa (2025) on AI and public-sector fraud detection and prevention. Their study revealed that machine learning significantly and positively influences the detection and prevention of public sector fraud. Similarly, the study is consistent with that of Omorogbe et al (2025), Aljunaid et al (2025), Reddy et al. (2024), that the adoption of AI technologies has the potential to significantly and positively enhance the effectiveness of fraud detection efforts by organisations. This shows that this technology can also contribute meaningfully to improving the detection of financial statement fraud, possibly through automated pattern recognition and the ability to process and analyse unstructured data such as text documents (Chen & Wong, 2023; Okoye, 2024). Kotagiri and Yada (2024) argue that NLP technologies have substantially improved fraud detection capabilities in organisations.

Data Analytics and Detection of Financial Statement Fraud: The results showed a positive and significant association between data analytic (AI) and detection of financial statement fraud in the public sector. This suggests that implementing the DTA technique in AI can enhance the detection of financial statement fraud in the public sector. This aligns with the research conducted by Chinda and Obiosa (2025) on AI and public sector fraud detection and prevention. Their study revealed that machine learning significantly and positively influences the detection and prevention of public sector fraud. Similarly, the study is consistent with that of Omorogbe et al (2025), Aljunaid et al (2025), Reddy et al., (2024), that the adoption of AI technologies has the potential to significantly and positively enhance the effectiveness of fraud detection efforts by organisations. This shows that this technology can also contribute meaningfully to improving detection of financial statement fraud possibly through automated pattern recognition and the ability to process and analyze unstructured data such as text documents (Chen & Wong, 2023; Okoye, 2024).

Data Mining and Detection of Financial Statement Fraud: The results showed a positive and significant association between data mining (AI) and detection of financial statement fraud in the public sector. This suggests that the implementation of DIM technique of AI can enhance the detection of financial statement fraud in the public sector. This concurs with the investigation conducted by Chinda and Obiosa (2025) on AI and public sector fraud detection and prevention.

Their study revealed that machine learning significantly and positively influences the detection and prevention of public sector fraud. Similarly, the study is consistent with that of Omorogbe et al (2025), Aljunaid et al (2025), Reddy et al., (2024), that the adoption of AI technologies has the potential to significantly and positively enhance the effectiveness of fraud detection efforts by organisations. This shows that this technology can also contribute meaningfully to improving detection of financial statement fraud, possibly through automated pattern recognition and the ability to process and analyze unstructured data such as text documents (Chen & Wong, 2023; Okoye, 2024). Hassan et al (2023) stress that the detection of financial statement fraud using data mining provides organisations with a strong technique for sustaining financial integrity.

Expert Systems and Detection of Financial Statement Fraud: The results showed a positive and significant association between expert systems (AI) and the detection of financial statement fraud in the public sector. This result concurs with the investigation conducted by Junaidi et al (2024) that examined fraud detection in public sector institutions in Indonesia. The study found that modern expert systems have a positive and significant effect on public sector fraud detection in Indonesia. The findings indicate that technology-driven expert systems improve auditors' ability to identify anomalies, patterns, and fraud indicators in government financial systems. The findings provide strong and significant evidence that expert systems do improve fraud detection in the public sector. As governments increasingly adopt data-driven technologies, EXS play a fundamental role in strengthening accountability, transparency, and uncovering hidden fraud patterns in modern public sector institutions.

Organisational Culture and Detection of Financial Statement Fraud: The results showed a positive and significant association between organisational culture and the detection of financial statement fraud in the public sector. The result is consistent with studies conducted by Soehaditama (2024), Anggraeni et al (2021), which provide that organisational culture has a positive and significant effect on fraud prevention. The empirical evidence strongly supports the view that organizational culture plays a positive and significant role in the detection of financial statement fraud. This implies that organisations that foster ethical values, accountability, and strong governance structures are better positioned to detect fraudulent financial reporting promptly. Also, this suggests that advanced AI fraud detection tools depend on a supportive organizational culture to attain optimal results.

Conclusion, Policy Implications, Limitations and Future Research

AI tools of machine learning, natural language processing, data analytics, data mining, and expert systems demonstrate a positive and statistically significant impact on the detection of financial statement fraud in the public sector. Empirical evidence shows that these AI tools enhance auditors' ability to identify anomalies, uncover hidden patterns, and analyse both structured and unstructured data, leading to more accurate and timely fraud detection. Their effectiveness is further strengthened when integrated with strong internal controls and governance systems, making them critical drivers of transparency and accountability in public sector financial management. In addition, organisational culture plays a positive and significant moderating role in the relationship between AI and the detection of financial statement fraud in the public sector. Empirical evidence indicates that while AI tools enhance fraud detection capabilities, their effectiveness is significantly strengthened in organisations characterised by strong ethical values, transparency, and accountability. A supportive organisational culture enables better adoption, proper utilisation, and critical interpretation of AI-driven insights, thereby amplifying their impact on fraud detection. Thus, organisational culture acts as a key enabler that determines how successfully AI tools translate into improved fraud detection outcomes.

The finding that organisational culture has a positive and significant moderating effect on the link between AI tools and the detection of financial statement fraud in the public sector has several important policy implications. First, public sector reforms should go beyond AI adoption and prioritise the development of a strong, ethical and innovative-supportive organisational culture. The government should ensure that values such as integrity, transparency, accountability, and openness to technological change are deeply embedded in public institutions. Secondly, policymakers should design and implement change management and digital transformation policies that explicitly address cultural readiness for AI adoption. Third, public sector institutions should institutionalize integrated governance frameworks that combine AI systems with ethical and behavioural standards. Fourth, regulatory and oversight bodies should include organisational culture assessments as part of digital audit frameworks. Finally, governments should invest in capacity building for ethical AI use in public administration, ensuring that employees not only understand how AI tools work but also how organisational values influence their effectiveness in detecting financial statement fraud.

Despite evidence that organizational culture significantly enhances the impact of AI tools on the detection of financial statement fraud in the public sector, several limitations remain in the current body of research. First, many studies are based on cross-sectional designs, which limit the ability to capture how organizational culture influences the effectiveness of AI tools over time. As a result, dynamic changes in culture and technology are not fully captured. Second, a large proportion of empirical evidence relies on survey-based data from auditors and accountants in the public sector. This introduces potential bias, as respondents may overstate the effectiveness of AI tools or the strength of organizational culture due to social desirability or institutional sensitivity around fraud-related issues. Thirdly, organizational culture is often measured as a single composite construct, which limits understanding of which specific cultural dimensions enhance the effectiveness of AI in fraud detection. Fourth, existing studies are concentrated in a limited number of public sector contexts, particularly in developing economies, which restricts the generalizability of findings across different governance systems and institutional environment.

To build on current research and address its limitations, future studies could consider the following directions:

1. Future research should adopt longitudinal and experimental designs to better capture causal associations and changes in the moderating role of organizational culture over time as AI systems evolve in the public sector.
2. Researchers should also consider using objective datasets, such as audit outcomes, fraud case records, and system-generated AI detection logs, to complement survey-based evidence and reduce self-reporting bias.

3. Future studies should disaggregate organizational culture into its core dimensions, enabling a more precise understanding of which cultural factors most strongly enhance AI effectiveness in fraud detection.
4. Further research should also explore the differential moderating effects of organizational culture across various AI tools, including machine learning, natural language processing, data analytics, data mining, and expert systems, to identify which combinations yield the highest fraud detection performance.

Acknowledgement

The researchers sincerely acknowledge the Tertiary Education Trust Fund (Tetfund) for its generous financial support, which made this study possible. Appreciation is also extended to the Management of Isaac Jasper Boro College of Education, Sagbama, Bayelsa State, for providing the institutional support and conducive environment necessary for the successful completion of this research.

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