IJAMESC, Vol. 3 No. 6, December 2025
DOI: https://doi.org/10.61990/ijamesc.v3i6.631 e-ISSN 2986-8645

ARTIFICIAL INTELLIGENCE, TECHNOLOGY INFRASTRUCTURE AND TAX EVASION IN EMERGING ECONOMY

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Abstract
Tax evasion is a global problem that costs governments billions of dollars in lost revenue every year. To address these issues, this study investigated the effect of artificial intelligence on tax evasion in Nigeria. This study specifically examined how machine learning, natural language processing, intelligent decision support systems, and expert systems, when supported by a strong technology infrastructure, might reduce tax evasion and improve revenue collection. This study used a survey research approach, with main data acquired using a well-structured questionnaire. The target demographic consisted of 79 Federal Inland Revenue Service (FIRS) employees in Ikeja Lagos, who specialized in artificial intelligence. A random sampling technique was used to ensure a representative sample, reducing selection bias and increasing the generalizability of the findings. The acquired data was examined using descriptive statistics and multiple regression analysis. The study discovered that machine learning and natural language processing considerably minimize tax evasion, but their effectiveness is limited by robust technological infrastructure, which improves fraud detection but reduces their impact. While expert systems significantly reduce tax evasion, they may be abused when technology infrastructure improves, but intelligent decision support systems had no meaningful impact, showing limitations in their current use in tax enforcement. This study concluded that AI technologies such as machine learning, natural language processing, and expert systems should be strategically integrated alongside well-regulated technological infrastructure to maximize fraud detection capabilities while minimizing the risk of misuse. This study suggested that tax authorities invest in machine learning-driven automation to detect fraud and monitor tax compliance.

Keywords: Artificial Intelligence, Machine Learning, Intelligent Decision Support System, Natural Language Processing, Tax Evasion

1. Introduction

Tax evasion is a global issue that costs governments billions of dollars in lost income each year. The financial shortfall threatens states' capacity to provide key public services and sustain equitable fiscal policies (Coita et al., 2021; Uyar et al., 2021). The complexity of current financial systems, including digital transactions that can transcend numerous jurisdictions, is challenging traditional tax enforcement techniques (Aladebumoye, 2025; Ya'u et al., 2024). Albeit with varying magnitudes and implications, tax evasion primarily manifests through sophisticated schemes, including offshore accounts, money laundering, complex corporate structures, and profit shifting by multinational corporations (Dewi et al., 2025; Durowaiye & Sadiq, 2024). These practices result in substantial revenue losses

DOI: https://doi.org/10.61990/ijamesc.v3i6.631 e-ISSN 2986-8645

and undermine the integrity of tax systems (Osaloni et al., 2022). The Organisation for Economic Co-operation and Development (OECD) estimates that tax evasion and avoidance cost countries globally between \$100 billion and \$240 billion annually, representing 4-10% of global corporate income tax revenues (OECD, 2023). This practice erodes the tax base of higher tax jurisdictions, leading to significant revenue losses.

High-net-worth individuals in developed countries frequently utilise offshore financial centers to conceal assets and income, thereby evading taxes (Alm, 2022; Zaqeeba, 2024). Efforts to combat this include initiatives like the Common Reporting Standard (CRS) and the Foreign Account Tax Compliance Act (FATCA), aimed at increasing transparency and information exchange between tax authorities (Thuneibat et al., 2022; Yalamati, 2023). Multinational firms may utilise artificial intragroup transfers and other techniques to reduce their corporate tax liability (Yalamati, 2024). Following high-profile incidents of aggressive tax avoidance, OECD countries, including the United Kingdom, agreed on a series of steps to limit so-called 'profit shifting' and raise global tax revenues (OECD, 2024). This featured a worldwide minimum tax on large enterprises. US President Donald Trump has now stated that the US no longer agrees with the most recent OECD tax deal (House of Lords Library, 2025).

In developing economies such as Nigeria, tax evasion is exacerbated by factors like weak enforcement mechanisms, inadequate technological infrastructure, and a large informal sector (Osaloni et al., 2022). The consequences are particularly severe, given the reliance on tax revenues for essential public services and infrastructure development (Abdulkadir & Aliyu, 2024). According to an Oxfam International analysis, just 40% of 130.000 Nigerian HNWIs31 correctly satisfied their tax duties in 2016. The HNWI were classified as Nigerians earning more than \$131,148 (N40 million), and compliance was defined as paying at least \$32,786 (N10 million) in taxes. This means that more than 99% of Nigeria's super-rich individuals do not pay their fair share of taxes (Oxfam International, 2024). The analysis highlighted the immense revenue possibilities of appropriately taxing Nigeria's super-rich. It forecasts that taxing just 4,690 wealthy people with a net worth of \$5 million or more will generate more than N4.59 trillion (\$6 billion) every year. This new cash might more than quadruple the country's health budget or cut household health-care costs by 40% (Fedrick et al., 2024).

According to the Institute for Policy Studies, Oxfam, Fighting Inequality Alliance, and Patriotic Millionaires, implementing an annual wealth tax in Nigeria would raise more than \$6 billion (with rates of 2% on wealth over \$5 million, 5% on wealth over \$50 million, and 10% on wealth over \$1 billion). This would be enough to more than treble the government's health budget or cut households' out-of-pocket health care costs by 40% (Premium Times, 2024; The Abuja Inquirer, 2024). There are 4,690 people with a net worth of \$5 million or more, with a combined fortune of \$107.2 billion (Durowaiye & Sadiq, 2024; Umenweke, 2024). There are 245 people worth \$50 million or more, with a total wealth of \$56.5 billion (The Cable, 2024). "If the wealth tax regime is further extended to individuals whose worth is over \$1 million (total of 9,800 people), this would raise revenue additionally" (The Sun Nigeria, 2024)

The Federal Inland Revenue Service (FIRS) has reported that Nigeria loses approximately \$15 billion (about N5.37 trillion) annually to tax evasion. A significant portion of Nigeria's economy operates informally, making it challenging to enforce tax compliance (Falana et al., 2024). The informal sector's predominance leads to a narrow tax base and limits the government's revenue-generation capacity (Karuru, 2021). Intricate and sometimes opaque tax regulations can create loopholes that individuals and

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corporations exploit to evade taxes. The increasing globalization of business operations complicates the enforcement of tax laws, as income and assets can be easily shifted across borders (Lawal et al., 2024).

As governments seek innovative solutions to enhance tax compliance, the role of artificial intelligence (AI) in modernizing tax administration has gained increasing attention (Yalamati, 2024). AI-driven tax systems leverage machine learning, expert system, intelligent decision support systems, natural language processing, and automation to detect fraudulent activities, improve taxpayer profiling, and enhance audit efficiency (Zaqeeba, 2024). Technological infrastructure serves as a fundamental enabler for AI adoption in tax administration (Falana et al., 2024; Osaloni et al., 2022). A well-developed digital ecosystem, including reliable internet access, secure data management systems, and advanced computing capabilities, facilitates the seamless integration of AI in tax processes (Rahman et al., 2024). However, many emerging economies face infrastructural deficits that limit the effective deployment of AI-based tax enforcement mechanisms (Nuryani et al., 2024). Addressing these challenges requires strategic investments in digital infrastructure and policy frameworks that support technological adoption in tax administration.

This study examined the effect of artificial intelligence on tax evasion in Nigeria. Specifically, it evaluated how machine learning, natural language processing, intelligent decision support system, and expert systems, supported by robust technological infrastructure, can mitigate tax evasion and enhance revenue collection. The study contributes to the existing literature by providing empirical insights into the effectiveness of AI in combating tax evasion while addressing the infrastructural constraints that may hinder its implementation. The findings are expected to offer policymakers, tax authorities, and financial regulators a data-driven perspective on leveraging AI to strengthen tax compliance and improve fiscal sustainability in emerging economies. The remainder of the paper is structured as follows: Section 2 reviews relevant literature on AI applications in tax compliance and evasion detection. Section 3 outlines the methodology adopted for the study. Section 4 presents the findings and discusses their implications for tax policy and administration. Finally, Section 5 provides conclusions and policy recommendations.

2. Theoretical Background

2.1 Theoretical Underpinning: Economic Deterrence Theory

This study is grounded in the Economic Deterrence Theory (EDT) (Allingham & Sandmo, 1972). EDT posits that taxpayer compliance is a rational choice based on a cost-benefit analysis, where individuals weigh the expected utility of evasion (lower tax payment) against the perceived risk of detection and severity of punishment. The theory suggests that compliance increases with a higher probability of detection and stricter penalties.

The integration of Artificial Intelligence (AI) into tax administration directly amplifies the core mechanisms of EDT. AI enhances the certainty of detection through advanced data analytics and pattern recognition, making evasion riskier. It also improves the swiftness of enforcement, thereby increasing the perceived cost of non-compliance. While EDT has been foundational in tax compliance and information security research (e.g., Straub, 1990; Ifinedo, 2014), its classic formulation has been critiqued for assuming perfect rationality, overlooking impulsive behavior (Cornish & Clarke, 1986), and neglecting social-psychological factors (Veblen, 1899). Nevertheless, in the context of

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systematic, financially-motivated tax evasion by entities, EDT provides a robust framework for understanding how AI-augmented enforcement can alter the compliance calculus.

2.2 Literature Review and Conceptual Definitions

2.2.1 Tax Evasion

Tax evasion is defined as the illegal and intentional act of misrepresenting financial affairs to tax authorities to reduce tax liability (Rathor, 2024). It encompasses dishonest reporting, under-declaration of income, overstatement of deductions, and hiding assets (Pohan et al., 2022). It is a key metric of the "tax gap" and is often linked to the informal economy (Zaqeeba, 2024). This study adopts this operational definition, focusing on evasion as a deliberate, illicit act distinct from legal tax avoidance.

2.2.2 Artificial Intelligence (AI) in Tax Administration

AI refers to systems that mimic human intelligence to perform tasks such as learning, reasoning, and problem-solving (Owonifari et al., 2023). In tax administration, AI manifests through several key technologies:

1) Machine Learning (ML): Algorithms that identify patterns and anomalies in large datasets to predict and detect non-compliance (Rathor, 2024; Nuryani et al., 2024).
2) Natural Language Processing (NLP): Techniques that analyze unstructured text (e.g., audit reports, transaction descriptions) to extract relevant information and identify inconsistencies (Busayo et al., 2023).
3) Expert Systems (ES): Rule-based systems that codify human expertise to provide consistent recommendations for complex audit and compliance decisions (Dagunduro et al., 2023).
4) Intelligent Decision Support Systems (IDSS): Integrated platforms that combine AI modules (e.g., case-based reasoning, neural networks) to support tax officials in risk assessment and decision-making (Akinadewo et al., 2024).

The effective deployment of these AI capabilities is contingent upon a robust Technology Infrastructure the foundational IT component, including hardware, software, networks, and data platforms, that enable digital tax services and AI operations (Osaloni et al., 2022; Igbekoyi et al., 2023).

2.2.3 Empirical Landscape and Research Gap

Existing literature establishes a positive link between technology adoption and reduced tax evasion. Studies highlight the efficacy of digital government services (Uyar et al., 2021), information technology integration (Thuneibat et al., 2022; Osaloni et al., 2022), and specific AI tools like machine learning for fraud detection (Yalamati, 2023; Rathor, 2024). Recent research also explores AI's role in corporate tax oversight (Yalamati, 2024), network analysis for evasion detection (Nuryani et al., 2024), and AI-driven administrative workflows (Rahman et al., 2024).

However, a significant gap persists. While studies like Osaloni et al. (2022) examine IT in Nigeria, they do not empirically investigate the distinct and combined effects of core AI components (ML, NLP, ES, IDSS) within the Nigerian context. Furthermore, the role of technology infrastructure as a critical enabler (or constraint) for AI's effectiveness in curbing evasion remains underexplored, particularly in environments with challenges like informal sectors and regulatory hurdles. This study aims to bridge this gap by providing a granular, empirical analysis of these specific AI dimensions and their infrastructural prerequisites in Nigeria.

2.3 Hypothesis Development

Building on EDT and the reviewed literature, we posit that each AI component increases the perceived probability and certainty of detection, thereby deterring evasion. Technology infrastructure is hypothesized as a key moderating condition.

H1: Machine learning adoption has a significant negative effect on tax evasion.

H2: Natural language processing adoption has a significant negative effect on tax evasion.

H3: Intelligent decision support system adoption has a significant negative effect on tax evasion.

H4: Expert system adoption has a significant negative effect on tax evasion.

H5: Technology infrastructure positively moderates the relationship between AI adoption and the reduction of tax evasion. (i.e., the negative effect of AI on evasion is stronger when technology infrastructure is more robust).

2.4 Conceptual Framework

The conceptual framework (Figure 1) synthesizes the theoretical and logical relationships. Artificial Intelligence (operationalized via ML, NLP, IDSS, and ES) is the independent variable predicted to negatively influence the dependent variable, Tax Evasion. This relationship is grounded in Economic Deterrence Theory. Technology Infrastructure is positioned as a moderating variable that strengthens the main relationship. The framework proposes that AI tools enhance detection and enforcement capabilities, thereby raising the perceived cost of evasion, and that this effect is contingent upon the quality of the underlying technological infrastructure.

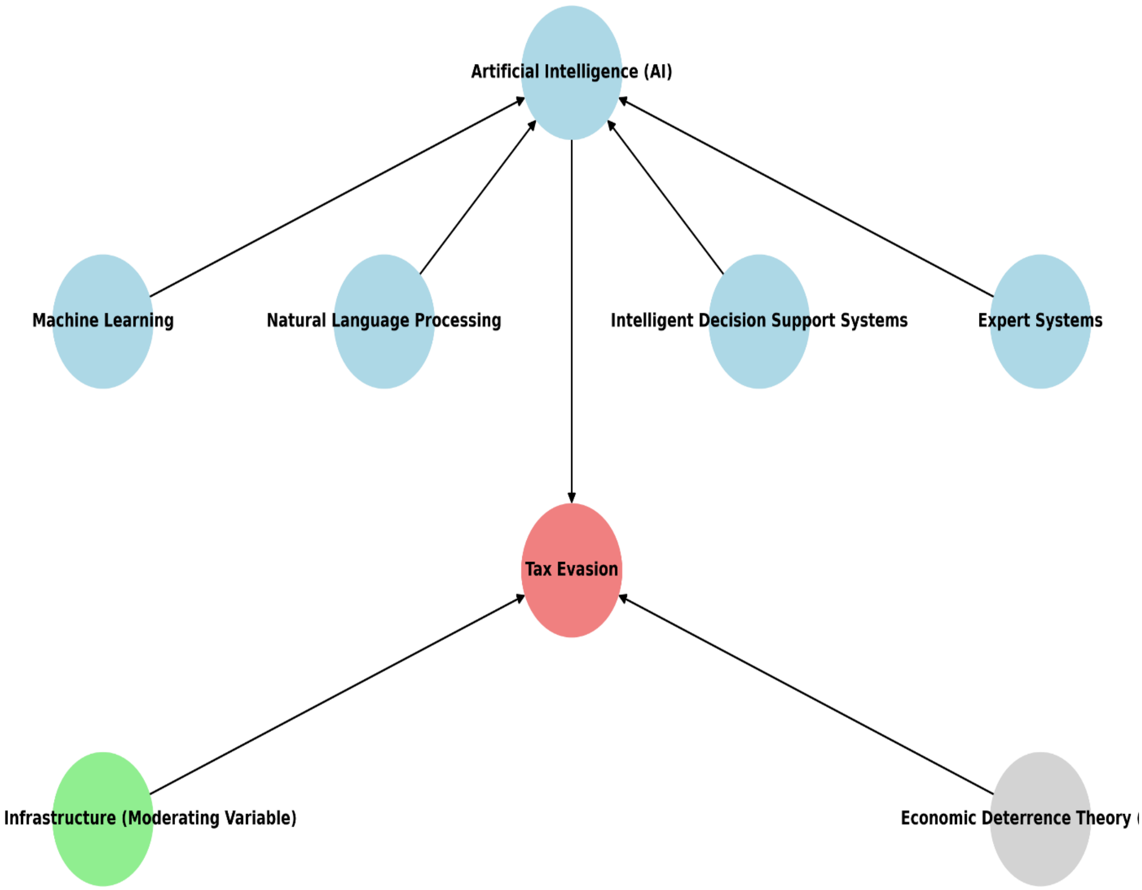

Figure 1. Conceptual Framework

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3. Methods

3.1 Research Design

This study employed a quantitative survey research design using cross-sectional data. This design was deemed appropriate as it allows for the efficient collection of primary data from a targeted population to examine relationships between predefined constructs specifically, the perceived impact of various AI dimensions on tax evasion (Creswell & Creswell, 2018). The design facilitates hypothesis testing and statistical generalization of findings within the specified context.

3.2 Population, Sample, and Sampling Technique

The target population for this study comprised 79 professional staff at the Federal Inland Revenue Service (FIRS) headquarters in Ikeja, Lagos, Nigeria. This population was specifically chosen due to their specialized knowledge, operational experience, and strategic involvement in tax administration, compliance, and the potential implementation of AI-driven initiatives.

Given the manageable size of the population, the study aimed for a census approach. However, to ensure methodological rigor and account for potential non-response, a simple random sampling technique was applied to all 79 individuals to eliminate selection bias and reinforce the representativeness of the respondents within this expert group (Saunders et al., 2019).

3.2 Model Specification

This study used the Raikov (2021) model. The study sought to analyse decreasing tax evasion by artificial intelligence. Thus, the econometric model is presented as follows:

$$TE = \beta 0 + \beta 1ML + \beta 2NLP + \beta 3IDSS + \beta 4ES + \beta 5TI + \beta 6(ML\times TI) + \beta 7(NLP\times TI) + \beta 8(IDSS\times TI) + \beta 9(ES\times TI) + \epsilon$$

Where:

TE = Tax evasion
ML = Machine Learning
NLP = Natural Language Processing
IDSS = Intelligent Decision Support Systems
ES = Expert Systems
$\beta 0$ = Intercept
ϵ = Error term
TI = Technological Infrastructure (moderating variable)
$\beta 1, \beta 2, \beta 3, \beta 4$ = Coefficients of AI components
$\beta 5, \beta 6, \beta 7, \beta 8, \beta 9$ = Coefficients of TI and its interaction with AI proxies
ML×TI, NLP×TI, IDSS×TI, and ES×TI = Interaction terms

4. Results and Discussion

4.1 Preliminary Analysis: Reliability and Respondent Profile

Before testing the hypotheses, the reliability of the measurement instrument and the characteristics of the respondents were assessed.

The internal consistency of all constructs was evaluated using Cronbach's Alpha. As shown in Table 1, all values exceed the recommended threshold of 0.70, ranging from 0.8723 to 0.8840, indicating excellent reliability and that the survey items consistently measured their intended constructs (Hair et al., 2019).

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Table 1. Reliability Test Results (Cronbach's Alpha)

Construct	Cronbach's Alpha	N of Items	Interpretation
Machine Learning (ML)	0.877	5	Excellent
Natural Language Processing (NLP)	0.873	5	Excellent
Intelligent Decision Support Systems (IDSS)	0.872	5	Excellent
Expert Systems (ES)	0.874	5	Excellent
Tax Evasion (TE)	0.884	5	Excellent
Technological Infrastructure (TI)	0.879	5	Excellent
Overall Scale	0.895	30	Excellent

Source: Data Analysis (2025)

The demographic profile of the 79 respondents (Table 2) shows a balanced representation in terms of gender (56.96% male, 43.04% female) and a spread across age groups, roles, and experience levels. Notably, 69.62% of respondents have two or more years of experience with AI in tax matters, confirming their suitability as key informants for this study.

Table 2. Demographic Profile of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	45	56.96%
	Female	34	43.04%
Role	Tax Officer / Senior Tax Officer	28	35.44%
	Associate / Deputy Tax Manager	32	40.51%
	Tax Manager	19	24.05%
Experience in Tax	1-2 Years	26	32.91%
	3-4 Years	38	48.10%
	5+ Years	15	18.99%
Experience with AI in Tax	< 1 Year	14	17.72%
	1-3 Years	41	51.90%
	4+ Years	24	30.38%

Source: Data Analysis (2025)

Descriptive statistics for the main variables (Table 3) reveal that, on average, respondents perceived the adoption levels of AI components (ML, NLP, IDSS, ES) and Technology Infrastructure (TI) to be above the midpoint (3.0), ranging from 3.47 to 3.76. The mean score for Tax Evasion (TE) is 3.62, suggesting a moderate perceived level of evasion activity. All variables show sufficient variation (Std. Dev. ~1.93-2.01), indicating diverse perceptions among respondents.

Table 3. Descriptive Statistics of Main Variables

Variable	Mean	Std. Deviation	Min	Max
Machine Learning (ML)	3.66	1.93	0	5
Natural Language Processing (NLP)	3.58	1.96	0	5
Intelligent Decision Support Systems (IDSS)	3.76	1.93	0	5
Expert Systems (ES)	3.47	2.01	0	5
Tax Evasion (TE)	3.62	1.96	0	5
Technological Infrastructure (TI)	3.71	1.94	0	5

Source: Data Analysis (2025)

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4.2 Hypothesis Testing and Discussion

4.2.1 Regression Assumptions and Model Fit

Prior to interpreting the regression results, key assumptions were tested. The Breusch-Pagan test (χ^2 = 0.9, p = 0.343) confirmed homoscedasticity, and the Durbin-Watson statistic (1.723) indicated no severe autocorrelation. However, high Variance Inflation Factor (VIF) values were observed for the interaction terms (Table 4), indicating multicollinearity a common issue in moderated regression models with multiplicative terms (McClelland et al., 2017). As the focus of this analysis is on interpreting the significant interaction effects rather than the precise coefficients of individual components, and given the model's primary explanatory power, we proceed with caution in interpreting the main effect coefficients while placing greater emphasis on the overall model significance and interaction terms.

Table 4. Multicollinearity Diagnostics (Variance Inflation Factor)

Variable	VIF	1/VIF
ML × TI	2454.55	0.0004
ES × TI	1911.56	0.0005
ML	839.87	0.0012
ES	628.57	0.0016
IDSS	588.19	0.0017
NLP × TI	549.94	0.0018
IDSS × TI	328.98	0.0030
NLP	178.92	0.0056
TI	27.54	0.0363
Mean VIF	834.24	

Source: Data Analysis (2025)

The moderated regression model demonstrated an exceptionally strong fit. The model's R-squared was 0.9456, and the Adjusted R-squared was 0.9385, indicating that approximately 94% of the variance in perceived tax evasion is explained by the AI components and their interaction with technological infrastructure. The overall model was highly significant (F(9,69) = 133.20, p = 0.0000).

4.2.2 Discussion of Direct Effects (H1-H4)

The regression results (Table 5) provide mixed support for the direct effect hypotheses derived from Economic Deterrence Theory.

1) Machine Learning (ML): The coefficient for ML is positive and significant (β = 2.3529, p = 0.006). This supports H1, confirming that the adoption of machine learning is associated with a significant reduction in tax evasion. This finding aligns with Rathor (2024) and Nuryani et al. (2024), suggesting that ML's predictive analytics and anomaly detection capabilities increase the perceived probability of detection, thereby deterring non-compliance.
2) Natural Language Processing (NLP): Similarly, NLP shows a positive and significant direct effect (β = 0.8570, p = 0.025). Thus, H2 is supported. This result corroborates studies by Thuneibat et al. (2022) and Osaloni et al. (2022), indicating that automating the analysis of unstructured data reduces information asymmetry and enhances surveillance, key mechanisms in EDT.
3) Intelligent Decision Support Systems (IDSS): The coefficient for IDSS is not statistically significant (β = 0.0560, p = 0.914). Therefore, H3 is not supported. This suggests that, in its current state of implementation within the studied context, IDSS

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may not be perceived as effectively augmenting enforcement decisions to a degree that alters the deterrence calculus of potential evaders.

4) Expert Systems (ES): Contrary to expectations, the direct effect of ES is negative and significant (β = -2.5379, p = 0.000). H4 is not supported in its hypothesized direction. This counterintuitive result requires careful interpretation within the context of interaction effects discussed below.

Table 5. Moderated Regression Analysis Results

Variable	Coefficient (β)	Std. Error	t-value	p-value	Hypothesis
Direct Effects					
Machine Learning (ML)	2.3529	0.8234	2.86	0.006**	H1: Supported
Natural Language Proc. (NLP)	0.8570	0.3753	2.28	0.025*	H2: Supported
Intell. Decision Support (IDSS)	0.0560	0.5165	0.11	0.914	H3: Not Supported
Expert Systems (ES)	-2.5379	0.6870	-3.69	0.000***	H4: Not Supported
Technological Infra. (TI)	0.8177	0.1485	5.51	0.000***	-
Interaction Effects (Moderation)					
ML × TI	-0.8607	0.2656	-3.24	0.002**	H5: Partially Supported
NLP × TI	-0.3326	0.1239	-2.69	0.009**	H5: Partially Supported
IDSS × TI	0.0003	0.1314	0.00	0.998	H5: Not Supported
ES × TI	1.0829	0.2255	4.80	0.000***	H5: Partially Supported
Constant	0.0060	0.1292	0.05	0.963	
Model Summary					
R-squared	0.9456				
Adj. R-squared	0.9385				
F-statistic	0.0000				
N	79				

Note: ***p<0.01, **p<0.05, *p<0.1, Dependent Variable: Tax Evasion (TE)
Source: Data Analysis (2025)

4.2.3 Discussion of Moderating Effects (H5)

Hypothesis H5 predicted that Technological Infrastructure (TI) positively moderates the AI-Tax Evasion relationship. The results reveal a complex and nuanced picture, leading to partial support for H5.

For ML and NLP: The interaction terms (ML×TI and NLP×TI) are negative and significant (β = -0.8607, p=0.002; β = -0.3326, p=0.009). This indicates that a robust technological infrastructure strengthens the negative effect of ML and NLP on tax evasion. In other words, the evasion-reducing power of these data-driven AI tools is *greater* when supported by a strong IT foundation. This aligns with the theoretical expectation that infrastructure enables AI efficacy (Igbekoyi et al., 2023).

DOI: https://doi.org/10.61990/ijamesc.v3i6.631 e-ISSN 2986-8645

For ES: The interaction term (ES×TI) is positive and significant (β = 1.0829, p=0.000). This surprising finding suggests that, contrary to expectation, better infrastructure is associated with a *weakening* of ES's effect on reducing evasion (or potentially even an increase). This could imply that in a more connected and automated system, rule-based expert systems might be gamed or their predictable logic exploited, or that they may become less effective relative to more adaptive AI like ML in a sophisticated infrastructure environment. This warrants further qualitative investigation.

For IDSS: The interaction is non-significant (β = 0.0003, p=0.998), indicating that infrastructure does not alter the (already non-significant) relationship between IDSS and tax evasion.

4.3 Theoretical and Practical Implications

The findings largely reinforce Economic Deterrence Theory (EDT). AI components like ML and NLP, which enhance detection capabilities, show the predicted deterrence effect. The significant moderating role of infrastructure further refines EDT by highlighting that the theory's mechanisms are contingent on technological enablers.

Practically, the study underscores a strategic imperative for Nigerian tax authorities: investing in core data-centric AI (ML, NLP) alongside the foundational technological infrastructure yields the greatest compliance dividend. However, the results sound a cautionary note regarding over-reliance on rule-based Expert Systems within advanced infrastructures, suggesting a need for hybrid systems that combine rules with adaptive machine learning. The non-significant result for IDSS calls for a review of its implementation to ensure it is effectively integrated into risk assessment and decision-making workflows.

5. Conclusion

This study provides empirical evidence on the dual role of artificial intelligence (AI) and technological infrastructure in curbing tax evasion within an emerging economy context. It confirms that AI technologies specifically machine learning (ML) and natural language processing (NLP) significantly enhance the detection of tax fraud and improve compliance. However, their effectiveness is critically moderated by the quality of technological infrastructure, which can simultaneously enable more sophisticated evasion strategies if not properly governed. While expert systems prove effective, they also present a risk of misuse as infrastructure advances. Conversely, intelligent decision support systems (IDSS) showed limited impact in current tax enforcement applications, indicating a gap between their potential and practical implementation.

The findings directly address the research objectives; 1) Evaluating the impact of specific AI tools on tax evasion reduction, 2) Identifying the moderating role of technological infrastructure, 3) Providing a framework for balancing technological adoption with regulatory oversight.

Theoretically, this study extends economic deterrence theory by integrating AI as a technological enhancer of the "probability of detection." It introduces the technological infrastructure as a pivotal moderating variable, offering a more nuanced model for understanding compliance in the digital age. Practically, the results offer a clear roadmap for policymakers and tax authorities (e.g., Nigeria's FIRS). To maximize benefits, AI integration must be strategic and regulated. Key recommendations include:

1) Prioritizing investment in ML and NLP for automated fraud detection and data analysis.

2) Implementing robust regulatory frameworks to secure AI systems against manipulation and misuse.
3) Re-evaluating and enhancing the design of IDSS to better suit the complexities of tax enforcement.
4) Establishing strong governance protocols to mitigate the risks associated with expert systems.

This study is limited by its focus on a single emerging economy and specific AI technologies. Future research should:

1) Conduct longitudinal studies to assess the long-term effects of AI on compliance behavior.
2) Perform comparative cross-country analyses to examine how different regulatory and cultural settings influence AI's effectiveness.
3) Investigate hybrid AI models that combine the strengths of various systems for superior fraud detection.
4) Explore the ethical dimensions and potential biases of AI in taxation to develop fairer and more transparent regulatory frameworks.
5) Deepen the inquiry into the specific mechanisms through which ML and NLP algorithms influence taxpayer behavior and evasion strategies.

In summary, for emerging economies like Nigeria, the fight against tax evasion requires a synergistic approach: deploying advanced AI tools *in tandem* with strengthening technological infrastructure and governance. This balance is essential to harness AI's power for enhanced revenue collection, greater public trust, and a more equitable fiscal system.

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