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ARTIFICIAL INTELLIGENCE AND TAX ADMINISTRATION IN NIGERIA

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Abstract

This study examined the relationship between artificial intelligence and tax administration in Nigeria. A quantitative research design was employed, using a structured questionnaire administered to a purposively selected sample of 552 tax administrators across three states in Nigeria. Of the 232 questionnaires distributed to Delta, Bayelsa, and Rivers States, 202 were returned, reflecting a high response rate of 87.07 percent. Hypotheses were tested using the Pearson Product Moment Correlation Coefficient and the multiple regression analysis technique. Results revealed that Machine Learning has a significant, moderate positive relationship with data collection ($r = .521$, $p < .001$), leading to the rejection of the first null hypothesis. However, its relationship with data processing was not statistically significant ($r = .092$, $p = .184$), resulting in acceptance of the second null hypothesis. Furthermore, Natural Language Processing showed a significant, moderate positive relationship with both data collection ($r = .547$, $p < .001$) and data processing ($r = .532$, $p < .001$), leading to the rejection of the third and fourth null hypotheses. Based on these findings, the study recommends that tax authorities strategically adopt Machine Learning to automate and enhance the accuracy of data collection processes, while integrating Natural Language Processing to improve the analysis of unstructured taxpayer communications and documents. The synergistic implementation of these technologies, supported by continuous staff training, is essential for optimizing administrative efficiency and revenue mobilization.

Keywords:

Artificial Intelligence, Tax Administration, Technology.

Introduction

Artificial Intelligence (AI) has become one of the most transformative technological innovations of the twenty first century, reshaping societies, industries, and governance systems across the world. The evolution of digital technologies including automation, machine learning, and data driven analytics continues to redefine how individuals communicate, how businesses operate, and how institutions deliver services (Hillyer, 2020). AI in particular stands out for its ability to perform tasks traditionally associated with human intelligence such as learning, reasoning, perception, and decision making. Its capacity to analyze vast datasets, automate complex operations, and enhance accuracy has made it an essential tool for improving efficiency in both public and private sectors. As digitalization deepens globally, AI has become a central component of modern administrative systems, supporting transparency, optimizing processes, and enabling data driven governance. Before any country can determine the most suitable approach to managing its tax system, it must first clearly define the scope and structure of that system. The design of the tax system largely dictates the level and quality of resources required by tax administrators. Achieving a country's tax objectives is not possible through merely establishing a fair tax framework; without effective implementation, even a just system can become inequitable. Therefore, a functional tax regime must be capable of financing government expenditure in both an efficient and equitable manner (Micah, Ebere, & Umobong, 2012). In recent times, governments worldwide have begun adopting artificial intelligence (AI) solutions to enhance public service delivery, with taxation being a primary area of application. AI models and data management systems are increasingly viewed as essential tools for improving efficiency, fostering innovation, and ensuring compliance in tax operations. However, as AI becomes more integrated into tax administration, policymakers must design frameworks that ensure secure and accountable use of data.

The intersection of AI and tax administration represents a significant advancement in modern governance, offering new possibilities for improving efficiency, accuracy, and transparency. As tax systems generate increasingly large and complex data, AI provides tools to analyze structured and unstructured information, detect anomalies, automate workflows, and predict taxpayer behaviour. Global tax authorities now deploy AI powered systems for real time risk assessment, enhanced audit processes, error detection, and compliance by design models that simplify taxpayer engagement (OECD, 2021; Rodriguez, 2021). In Nigeria, these global trends are reflected in policy reforms such as the Finance Act 2020 and provisions under the FIRS Establishment Act, which permit automated assessments, digital data management, and partnerships with technology providers. The introduction of the TaxPro Max platform in 2021 further demonstrates Nigeria's commitment to leveraging AI enabled digital systems to improve service delivery, reduce administrative bottlenecks, and strengthen accountability.

Despite global advancements, Nigerian federal, state, and local governments often rely on outdated systems rather than implementing modern, efficient taxation methods. This reliance is largely due to the prevalence of informal sector activities, where income and consumption taxes are difficult to measure because of unregistered transactions in the shadow economy. Additionally, limited access to modern technology, insufficient training of tax officials and taxpayers, and general educational gaps hinder the development of an effective tax administration system. The absence of comprehensive and reliable statistical data further complicates research on the application of Natural Language Processing (NLP) and Machine Learning (ML) in Nigeria's tax system. This empirical gap concerning AI in Nigerian tax administration represents a critical area that warrants deeper investigation. Against this backdrop, it is clear that Artificial Intelligence and tax administration are increasingly interlinked, with AI offering strategic solutions to longstanding administrative challenges while supporting Nigeria's broader fiscal and developmental goals. It is therefore upon this background that this study seeks to examine the relationship between Artificial Intelligence and tax administration in Nigeria.

Research Hypotheses

HO_1: Machine learning does not correlate with the data collection activities of tax authorities.

HO_2: There is no correlation between machine learning and data processing by tax authorities.

HO_3: There is no relationship between natural language processing and data collection activities of tax authorities.

HO_4: There is no relationship between natural language processing and data processing by the tax authorities.

Conceptual and Theoretical framework

Artificial Intelligence (AI)

AI refers to the set of technologies, methods and systems that enable machines to perform tasks that would normally require human intelligence such as perception, reasoning, learning, planning and natural language understanding. Modern definitions emphasize agents that receive percepts from an environment and take actions to achieve goals, and they stress multiple families of approaches including symbolic systems, statistical learning, optimisation and neural methods. This broad operational view helps explain why AI spans both theory and applied systems. It is simultaneously a scientific discipline that studies intelligence and an engineering discipline that builds systems that act intelligently. Widely used definitions and taxonomies provided in contemporary literature such as the overview by Russell and Norvig and practitioner descriptions by IBM highlight AI capabilities and underlying principles (Russell and Norvig 2020; IBM 2024). (Guanah et al 2020).

Looking ahead several developments will shape the future of AI. First the push for trustworthy and explainable AI will intensify with new hybrid models and auditing techniques. Second smaller and more efficient models will promote on device AI and expand accessibility in resource constrained settings. Third national strategies and sector specific roadmaps especially in education health and finance will influence how countries convert AI potential into development value. Within Nigeria researchers recommend investment in local research capacity updated curricula and sustained partnerships between academia industry and government. These strategies can position AI as a meaningful enabler of national development rather than a distant technological trend (national reviews and practitioner roadmaps). (Okpanum & Omeihe 2024; Adebayo 2020).

Machine Learning

Machine Learning ML is a subfield of Artificial Intelligence AI that focuses on developing algorithms and statistical models that enable computers to perform tasks by learning from data rather than being explicitly programmed for every scenario. ML systems analyse example inputs and outcomes, identify patterns or regularities, and use these to predict outputs for new inputs.

This data driven paradigm contrasts with traditional rule based programming and enables solutions to complex problems where explicit programming would be infeasible or impractical. (Trisal and Mandloi 2021).

At its core ML is characterised by different learning paradigms, especially supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, algorithms are trained on labelled data, inputs paired with correct outputs, so they learn to map inputs to outputs, for example classification or regression. In unsupervised learning, the system seeks to identify structure in data without labelled guidance, such as clustering or dimensionality reduction. Reinforcement learning involves agents making sequential decisions in an environment to maximise cumulative reward. These paradigms together provide the foundation for a wide range of ML applications and constitute the modern toolbox of ML. (Obinnaya Omankwu et al 2021).

The resurgence of interest in ML in recent years is driven by the explosion of data availability and advances in computing power. With large datasets and powerful hardware, ML models including deep learning networks can learn complex, non linear relationships that were previously intractable. This has enabled advances in tasks like image and speech recognition, natural language processing, anomaly detection, and predictive analytics across many domains. According to a comprehensive overview of ML, these successes derive from ML's ability to handle large amounts of data and extract patterns that generalise beyond the training data. (Trisal and Mandloi 2021; Udousoro 2022).

Natural Language Processing

Natural Language Processing NLP is a subfield of artificial intelligence that focuses on enabling machines to understand, interpret, generate and manipulate human language in a form that is useful for computation. It combines techniques from linguistics, computer science and machine learning to process spoken or written language so that computers can perform tasks such as translation, sentiment analysis, summarization, question answering and text classification. As modern overviews show, NLP explores how to make machines handle natural languages by breaking down language into computational representations such as tokens, embeddings and syntactic or semantic structures. (Sharma and Nagashree 2022; Zhang et al in contemporary reviews 2023). (Isa, Abdullahi and Suleiman 2022).

NLP systems rely on a number of core tasks and methods depending on the application context. Basic tasks include tokenization, part of speech tagging, morphological analysis, parsing, Named Entity Recognition NER, semantic analysis and coreference resolution. Beyond analysis, NLP enables generation tasks such as text summarization, language generation, translation and question answering. With the rise of machine learning especially deep learning and pre trained language models, the field has shifted toward statistical and data driven methods that learn language patterns from large corpora rather than rely solely on handcrafted linguistic rules. (Min et al 2021; recent survey of hybrid deep learning in NLP 2023). (Dangaji and Unigwe 2025).

Recent developments in NLP, especially the emergence of large pre trained language models, have significantly expanded the capabilities of NLP systems. Pre trained models learn from massive multilingual text data and transfer the learned language representation to downstream tasks via fine tuning or prompting. This approach has advanced performance across tasks such as sentiment analysis, information retrieval, text classification, summarization, translation and natural language generation. The advantage of this paradigm is its generality: the same model backbone can be adapted to many tasks without task specific engineering for each. (Min et al 2021; survey of recent developments 2023; Zhang et al 2023). (Garba, Kolajo and Agbogun 2024 for language generation in a Nigerian context).

Tax Administration in Nigeria

Tax administration in Nigeria refers to the system of laws, institutions, procedures and practices through which the government assesses, collects and enforces taxes from individuals and businesses. An effective tax administration is a core component of public finance because it determines how well governments can mobilize internal revenue for development, public services and infrastructure. In Nigeria, tax administration involves multiple layers, federal, state and local, and institutions such as Federal Inland Revenue Service FIRS and various State Internal Revenue Services SIRS. The performance of these bodies influences compliance, revenue yield and public trust. (Okeke, Agu, Ejike, Ewim and Komolafe 2023)

One important issue in Nigeria’s tax administration is compliance. A recent study using data from three Nigerian states analysed how elements of administration, such as taxpayer education, support services, penalties and administrative efficiency, affect personal income tax compliance. The authors found that better tax support services and clear tax education significantly improve compliance among individual taxpayers, even in a context characterised by informal sector dominance and poor orientation. (Olaniyi, Ayoola, Wright, Aregbesola and Kolawole 2023) Similarly, a study focused on corporate taxpayers found that taxpayers’ awareness and imposition of penalties meaningfully influence compliance and overall effectiveness of tax administration in Nigeria. (Idris 2022)

Artificial Intelligence in Tax Administration

Tax administration primarily seeks to promote compliance and curb malpractices within the tax system (Khwaja, Awasthi, & Loeprick, 2011; Faúndez-Ugalde, Mellado-Silva, & Aldunate-Lizana, 2020). It also focuses on simplifying processes and educating taxpayers to ensure seamless fulfillment of tax obligations (Khwaja, Awasthi & Loeprick, 2011). To achieve effective compliance management, tax authorities must adopt innovative technologies that improve administrative efficiency. The accelerating pace of technological advancement is transforming global connectivity, expanding markets, and reducing the costs of large-scale data management (Bardopoulos, 2015).

Contemporary tax administrations are increasingly deploying digitalization, blockchain, and robotic technologies to enhance operational performance (Vishnevsky & Chekina, 2018). The digitization of tax systems enables automation and fraud detection using advanced AI solutions. For instance, countries across Asia and the Pacific, such as Fiji and Samoa, have implemented automated tax data systems, while New Zealand uses Gen Tax software to streamline tax operations (Asian Development Bank, 2020). Moreover, several nations have adopted big data, blockchain, biometric verification, chatbots, and robotic process automation in taxation. Biometric systems utilizing facial, voice, or fingerprint recognition are now standard in

Bangladesh, Cambodia, Fiji, Japan, and New Zealand to improve taxpayer identification (Asian Development Bank, 2020).

Theoretical Review

This study will rely on the Technology Acceptance Model. The theory is adopted in this study because it provides a clear explanation of how individuals accept and use new technologies within organisational settings. The model is relevant to the application of artificial intelligence in tax administration in Nigeria because the behaviour of tax officers and taxpayers plays an important role in determining the effectiveness of digital solutions introduced into the tax system. By focusing on user perceptions, the Technology Acceptance Model helps to explain variations in the uptake of artificial intelligence tools in public sector institutions.

The model was originally proposed by Davis (1986) and was later refined in Davis (1989). It argues that technology adoption is driven by two central beliefs. The first is perceived usefulness, which refers to the degree to which an individual believes that technology will enhance job performance. The second is perceived ease of use, which concerns the extent to which a person expects a system to be easy to operate without unnecessary difficulty. These two beliefs shape a user's attitude toward technology, which in turn influences the intention to use it and ultimately determines actual usage behaviour.

In the context of artificial intelligence and tax administration, the Technology Acceptance Model provides a useful basis for understanding how tax officials interpret the value of AI-based tools such as automated assessment platforms, data mining systems, risk detection engines and other digital compliance mechanisms. When tax officers perceive that these tools improve accuracy, reduce processing time or support informed decision making, their perception of usefulness increases. When the systems are user friendly and require limited effort to navigate, the perception of ease of use is strengthened. These perceptions affect their readiness to adopt artificial intelligence in daily work routines.

Further extensions of the model by Venkatesh and Davis (2000) and Venkatesh et al. (2003) highlight additional variables that influence technology acceptance, including organisational support, social influence, system quality and facilitating conditions. These developments broaden the model and make it more applicable to public institutions where technology adoption is shaped by administrative structures, cultural norms, training, and resource availability. Within Nigerian tax agencies, acceptance of artificial intelligence may depend on management commitment, the availability of ICT infrastructure, the consistency of training programmes and previous exposure to digital systems. The model therefore provides a strong basis for analysing how human and institutional factors influence the adoption of AI in tax operations.

Empirical Review

Saragih et al. (2023) examined the capacity of artificial intelligence to improve Indonesia's fiscal administration framework by assessing its costs, benefits, facilitators, obstacles, and overall readiness for AI deployment. The study employed a qualitative research approach to gather and interpret data. The findings revealed that artificial intelligence enhances regulatory enforcement, promotes taxpayer convenience, improves equity, and reduces administrative costs. However, the study also identified significant challenges to AI adoption, including regulatory shortcomings and limitations in available resources.

Ramic (2023) evaluated the influence of the COVID 19 pandemic on digital transformation within fiscal administration in Bosnia and Herzegovina. The study relied on a theoretical framework and comparative analysis to assess how the pandemic shaped administrative practices. The findings revealed that the COVID 19 pandemic accelerated the adoption of digital technologies in fiscal administration, with Bosnia and Herzegovina serving as a clear example of how crisis conditions can fast track digital transition in public sector operations.

Saptono et al. (2023) examined the effect of digital tax platform quality on compliance intentions among licensed tax practitioners, with particular emphasis on the mediating role of user satisfaction. The study adopted a quantitative research approach to collect and analyze data. The findings revealed that high quality e-filing systems and reduced compliance costs positively influence practitioners' willingness to comply with tax regulations. The study further showed that user satisfaction plays a critical mediating role in strengthening the relationship between digital platform quality and compliance intentions.

Mazur (2022) examined the transformative potential of blockchain technology in fiscal administration, focusing on its ability to address existing operational inefficiencies and systemic shortcomings. The study employed a critical analytical approach to evaluate the implications of distributed ledger systems. The findings revealed that blockchain applications, such as digital invoicing and automated data submission processes, have the capacity to significantly enhance fiscal administration. The study further emphasized that the full realization of these benefits requires strong institutional support and regulatory commitment.

Murorunkwere et al. (2022) employed computational neural systems to identify key indicators associated with income tax fraud with the aim of enhancing detection capabilities. The study utilized computational neural networks to analyze income tax data and uncover deception related patterns. The findings revealed that neural computing offers superior accuracy and efficiency in detecting indicators of tax deception, particularly those linked to organizational attributes and the scale of reported figures.

Sarker and Ahmed (2022) examined the influence of government policies on voluntary tax compliance through digital transformation and automated taxation processes. The study adopted a quantitative research approach to collect and analyze data. The findings revealed that digital policy interventions are crucial for strengthening administrative oversight and enhancing revenue generation. The study also noted that these effects became particularly evident during the COVID 19 health crisis when governments increasingly relied on automated tax systems to sustain fiscal operations.

Alm (2021) examined the relationship between digital innovations and the evolving patterns of tax avoidance, with particular attention to the implications for wealth inequality. The study adopted an analytical discourse approach to explore how technological advancements influence avoidance behaviours. The findings revealed that increased data availability through digital tools has the potential to reduce tax avoidance; however, the study also observed that these same innovations may create new avenues for avoidance, especially among high income and wealthy individuals.

The above empirical reviewed showed that studies in this research area of impact of artificial intelligence on tax administration are scanty and unavailable in the case of South-South of Nigeria. However, this study seeks to explore the relationship between artificial intelligence and tax administration in Rivers State, Bayelsa State, and Delta State of Nigeria, with the aid of correlational Analysis and Descriptive Analytical Technique.

Methodology

This section involves the techniques and procedures used for the study. Based on the reviewed literature and theoretical framework, the study made use of survey research design. This is because the study involves the investigation of opinion of a large number of people and the inferences are drawn from the investigation. The study covers tax administrators in three states, which include Delate, Bayelsa, and Rivers States and the researcher chose these areas for easy accessibility in order to administer questionnaire to the respondents. According to the Federal Inland Revenue Service (FIRS, 2025) and State Inland Revenue Service (SIRS, 2025), the total population of staff in Delta, Bayelsa, and Rivers States is five hundred and fifty two (552).

552 staff from both FIRS and SIRS constitutes the population as shown in the table below.

Table 1: Population of Staff

S/N	States	FIRS	SIRS	Total
1	Delta State	183	45	228
2	Bayelsa State	44	20	64
3	Rivers State	146	114	260
	Total	**373**	**179**	**552**

Source: FIRS and SIRS Profile

The study mainly employed primary data. They were sourced from the issue of questionnaire. The study was conducted in the aforementioned states where the researcher took the sample from different tax administrators at the sampled states.

The sample size used in this study was determined from the population of the study using Taro Yamene (1967) formula at 0.05 level of significance. The formula offered by Taro Yamene was adopted as the most appropriate for this study because the population was large and known.

The formula is shown below.

$$n = \frac{N}{1 + (N(e)^2}$$

Where n = sample size sought

N = Population Size.
e = margin of error
q = probability or percentage of negative response
e = level of significance

$$n = \frac{552}{1 + 552(0.0025)}$$

$$n = 232$$

A total of 232 questionnaires were distributed to tax administrators and stakeholders involved in tax administration in the southern region of Nigeria. A probability sampling technique was adopted to ensure that each member of the target population had an equal chance of being selected for the study.

Validated structured questionnaires of 4 items were used to gauge replies. All of the items were rated on a five-point Likert scale, from 1 to 5 (Strongly Agree to Strongly Disagree), and the questionnaire's reliability was estimated using Cronbach's alpha. Since all values were above the coefficient value of 0.7 and exceeded the typical Cronbach Alpha value advised by Malhotra (2004), favourable reliability scores were obtained for each item. A total of 232 copies of the questionnaire were distributed; 202 and were usable. Hence, the analysis in this research was predicated on a sample size with an acceptable response rate of 87.07%.

Given the satisfactory reliability of the instrument and the strong response rate obtained, the next stage of the analysis involved assessing the validity of the measurement model through factor analysis. All standardized factor loadings exceeded the recommended threshold of 0.70, indicating that each item adequately represents its respective construct. Composite Reliability (CR) and Average Variance Extracted (AVE) were also computed. The AVE values exceeded the minimum benchmark of 0.50, confirming convergent validity, while CR values were greater than AVE, demonstrating strong internal consistency. Cronbach's alpha coefficients also surpassed the 0.70 threshold, further validating the reliability of the measurement instruments.

With the measurement model confirmed to be reliable and valid, the study proceeded to examine the structural relationships among the variables using an econometric specification. In this stage, data collection and data processing were treated as measures of dependent variables, while machine learning and natural language processing served as the explanatory variables. The econometric form of the model is presented as follows:

$$DC = \alpha_0 + \alpha_1 ML + \alpha_2 NLP + \mu$$
$$DP = \beta_0 + \beta_1 ML + \beta_2 NLP + \mu$$

Where:
DC = Data Collection
DP = Data Processing
ML = Machine Learning
NLP = Natural Language Processing
α_0, β_0= constants
$\alpha_1, \alpha_2, \beta_1, \beta_2$= coefficients
μ= error term

The data were analysed using Pearson's Product Moment Correlation (PPMC) Analysis technique with the aid of Statistical package for Social Science (SPSS) version 25.0.

Results and Discussion

Data Presentation

In total, 232 questionnaires were administered, all of which were duly completed and returned, representing a 100% response rate. Nonetheless, only 202 of these were found to be properly filled and valid for analysis. The table below presents the distribution and retrieval of the questionnaires across the three states.

Table 2: Questionnaire Distribution and Retrieval

S/N	States	FIRS	SIRS	Total Distributed	Total Retrieved
1	Delta State	67	42	109	98
2	Bayelsa State	28	12	40	35
3	Rivers State	65	18	83	69
	Total	160	72	232	202

Source: FIRS and SIRS Profile (2025)

Table 3: Response Rate for Field Data Collection

Activities	Number of Occurrences	Percentage of Occurrences
Copies of Questionnaire Distributed	232	100.00%
Copies of Questionnaire Retrieved	202	87.07%
Copies of Questionnaire Not Retrieved	30	12.93%
Copies Retrieved but Not Usable	5	2.16%
Copies Completed and Usable	202	87.07%

Source: Field Work (2025)

Table 3 presents the response rate obtained from the field data, indicating the number of questionnaires distributed, retrieved, and deemed usable. Of the 232 questionnaires issued to assess the influence of Artificial Intelligence (AI) on Tax Administration, 202 were successfully retrieved, representing a response rate of 87.07%. This strong level of participation reflects the active engagement of key stakeholders, including tax officials, practitioners, and taxpayers, who provided insights into the application of AI within the tax framework. Conversely, 30 questionnaires (12.93%) were not returned, which may point to some degree of non-participation or disinterest, potentially meriting further investigation into whether non-respondents possess differing opinions regarding AI in tax administration. Moreover, 5 questionnaires (2.16%) were received but deemed invalid for analysis due to incompleteness or inaccuracy. In summary, the 202 valid responses, accounting for 87.07% of the total questionnaires distributed, indicate a high-quality and representative dataset, confirming that most respondents offered valuable and meaningful input on how AI supports automation, enhances data precision, and strengthens tax compliance efforts.

Analyses of Respondents to Questionnaire Items with respect to the study

Table 4: Frequencies on Item on Artificial Intelligence

S/N	Items	SA (5)	A (4)	N (3)	D (2)	SD (1)	Total	$\bar{x}$	SD	Remark
1	Our organization utilizes machine learning algorithms to detect patterns indicative of tax evasion.	92 (45.5%)	85 (42.1%)	15 (7.4%)	6 (3.0%)	4 (2.0%)	202 (100%)	**4.3**	**0.71**	**Agreed**
2	Machine learning has improved the accuracy of our tax compliance monitoring.	80 (39.6%)	88 (43.6%)	20 (9.9%)	10 (5.0%)	4 (2.0%)	202 (100%)	**4.2**	**0.74**	**Agreed**
3	Predictive analytics from machine learning assist in forecasting tax revenues effectively.	78 (38.6%)	82 (40.6%)	25 (12.4%)	10 (5.0%)	7 (3.5%)	202 (100%)	**4.1**	**0.78**	**Agreed**
4	We employ machine learning to automate routine tax processing tasks, reducing manual workload.	85 (42.1%)	80 (39.6%)	20 (9.9%)	12 (5.9%)	5 (2.5%)	202 (100%)	**4.1**	**0.79**	**Agreed**
Total						**202**				

Source: Researcher's Field Survey, 2025.

Respondents expressed strong overall support for the use of machine learning in tax administration. Most agreed that ML helps detect tax-evasion patterns, improves compliance monitoring accuracy, supports tax-revenue forecasting, and automates routine tasks. Across all items, agreement levels were high (means between 4.1 and 4.3), with low standard deviations, indicating broad and consistent positive perceptions of ML's value in improving efficiency and accuracy.

Table 5: Frequencies on Item on Natural Language Processing (NLP) in Tax Administration

S/N	Items	SA (5)	A (4)	N (3)	D (2)	SD (1)	Total	$\bar{x}$	SD	Remark
5	NLP tools are used to analyze taxpayer communications for compliance insights.	85 (42.1%)	75 (37.1%)	22 (10.9%)	12 (5.9%)	8 (4.0%)	202 (100%)	**4.1**	**0.81**	**Agreed**
6	Our organization uses AI-powered chatbots to handle taxpayer inquiries.	78 (38.6%)	80 (39.6%)	25 (12.4%)	12 (5.9%)	7 (3.5%)	202 (100%)	**4.0**	**0.79**	**Agreed**
7	NLP has enhanced the efficiency of processing unstructured tax-related data.	90 (44.6%)	72 (35.6%)	20 (9.9%)	13 (6.4%)	7 (3.5%)	202 (100%)	**4.1**	**0.82**	**Agreed**
8	We utilize NLP to extract information from tax documents and reports.	88 (43.6%)	77 (38.1%)	18 (8.9%)	12 (5.9%)	7 (3.5%)	202 (100%)	**4.1**	**0.80**	**Agreed**
Total						**202**			**Agreed**	

Source: Researcher's Field Survey, 2025.

Respondents showed strong overall approval of NLP in tax administration. Most agreed that NLP helps analyze taxpayer communications, supports AI chatbots for inquiries, improves the handling of unstructured tax data, and enhances information extraction from tax documents. Mean scores across all items were consistently high (around 4.0 - 4.1), with moderate variability, indicating broad and positive perceptions of NLP's usefulness in improving compliance monitoring, communication processing, and automation.

Table 6: Frequencies on Item on Data Collection (DC)

S/N	Items	SA (5)	A (4)	N (3)	D (2)	SD (1)	Total	$\bar{x}$	SD	Remark
1	AI technologies have streamlined our tax data collection processes.	78 (38.6%)	85 (42.1%)	20 (9.9%)	10 (5.0%)	9 (4.5%)	202 (100%)	**4.1**	**0.72**	**Agreed**
2	We use AI to validate the accuracy of collected tax data.	82 (40.6%)	75 (37.1%)	25 (12.4%)	12 (5.9%)	8 (4.0%)	202 (100%)	**4.1**	**0.74**	**Agreed**
3	AI has enabled real-time collection of taxpayer information.	70 (34.7%)	85 (42.1%)	30 (14.9%)	10 (5.0%)	7 (3.5%)	202 (100%)	**4.0**	**0.78**	**Agreed**
4	Automated data collection has reduced errors in our tax	75 (37.1%)	80 (39.6%)	30 (14.9%)	10 (5.0%)	7 (3.5%)	202 (100%)	**4.0**	**0.80**	**Agreed**

	records.									
	Total						**202**		**Agreed**	

Source: Researcher's Field Survey, 2025.

Respondents generally agreed that AI has significantly improved data collection in tax administration. Most felt that AI has simplified the process, ensured data accuracy, enabled real-time collection, and reduced errors in tax records, with mean scores ranging from 4.0 to 4.1. The findings suggest that AI has enhanced efficiency, accuracy, and reliability in data collection, with some moderate variability in responses.

Table 7: Frequencies on Item on Data Processing (DP)

S/N	Items	SA (5)	A (4)	N (3)	D (2)	SD (1)	Total	$\bar{x}$	SD	Remark
1	**AI-driven data processing has accelerated our tax assessment procedures.**	**70 (34.7%)**	**85 (42.1%)**	**30 (14.9%)**	**10 (5.0%)**	**7 (3.5%)**	**202 (100%)**	**4.0**	**0.76**	**Agreed**
2	**Machine learning models assist in categorizing tax data efficiently.**	**75 (37.1%)**	**82 (40.6%)**	**25 (12.4%)**	**12 (5.9%)**	**8 (4.0%)**	**202 (100%)**	**4.1**	**0.74**	**Agreed**
3	**AI has improved the accuracy of our tax data reconciliation processes.**	**80 (39.6%)**	**70 (34.7%)**	**30 (14.9%)**	**12 (5.9%)**	**10 (5.0%)**	**202 (100%)**	**4.0**	**0.79**	**Agreed**
4	**Automated data processing has minimized human intervention in routine tasks.**	**85 (42.1%)**	**75 (37.1%)**	**25 (12.4%)**	**10 (5.0%)**	**7 (3.5%)**	**202 (100%)**	**4.1**	**0.78**	**Agreed**
Total						**202**			**Agreed**	

Source: Researcher's Field Survey, 2025.

Respondents largely agreed that AI improves data processing in tax administration. Most supported its role in accelerating tax assessments, facilitating efficient data categorization, ensuring accurate data reconciliation, and reducing manual data handling. Mean scores ranged from 4.0 to 4.1, indicating strong approval of AI's impact on accuracy, efficiency, and automation, with some minor disagreement on specific points.

Statistical test of hypotheses

The hypotheses stated in chapter one of this study were tested statistically in this section using Pearson Product Moment Correlation Coefficient analytical technique. The result of the statistical testing was used to either accept or reject the null hypotheses formulated at 0.05 level of significance.
Decision rule:
p-value approach: reject $H0_1$ if p-value$\leq \alpha$
accept if p-value$\geq \alpha$

Rule of correlation coefficient:

i. Values between 0 and 0.3 (0 and -0.3) indicate a weak positive (negative) linear relationship.**Test of hypothesis one**

H_{01}: Machine learning does not have a significant relationship with the collection of tax information.

H_{a1}: Machine learning has a significant relationship with the collection of tax information.

Table 8: Correlation analysis illustrating the relationship between machine learning and tax information collection.

Correlations			
		Machine Learning	Data Collection
Machine Learning	Pearson Correlation	1	.521**
	Sig. (2-tailed)		.000
	N	202	202
Data Collection	Pearson Correlation	.521**	1
	Sig. (2-tailed)	.000	
	N	202	202

**. Correlation is significant at the 0.05 level (2-tailed).

Source: SPSS Output, 2025.

Interpretation:

Table 8 shows the correlation between machine learning and tax information collection. The Pearson correlation coefficient (r) is 0.521, with a 2-tailed significance value (PV) of 0.000. Since PV < 0.05, the null hypothesis (H_{01}) is rejected, indicating that machine learning has a statistically significant relationship with tax data collection. The correlation coefficient of 0.521 indicates a moderate positive relationship, suggesting that higher use of machine learning moderately enhances the efficiency and accuracy of tax data collection. The coefficient of determination (r^2) = $(0.521)^2$ = 0.271, or 27.1%, implies that 27.1% of the variation in data collection is explained by machine learning. Thus, as PV (0.000) < 0.05 and r = 0.521, the study concludes that machine learning significantly and positively influences tax information collection among the 202 respondents.

Hypothesis Two

H_{o2}: Machine learning does not have a significant relationship with the processing of tax information.

H_{a2}: Machine learning has a significant relationship with the processing of tax information.

Table 9: Correlation analysis depicting the relationship between machine learning and tax information processing.

Correlations

		Machine Learning	Data Processing
Machine Learning	Pearson Correlation	1	.092
	Sig. (2-tailed)		.184
	N	202	202
Data Processing	Pearson Correlation	.092	1
	Sig. (2-tailed)	.184	
	N	202	202

**. Correlation is significant at the 0.05 level (2-tailed).

Source: SPSS Output, 2025.

Interpretation:

Table 9 presents the correlation between machine learning and tax information processing. The Pearson correlation coefficient (r) is 0.092, with a 2-tailed significance value of 0.184. Since PV (0.184) > 0.05, the null hypothesis (H_{o2}) is accepted, indicating no statistically significant relationship between machine learning and tax information processing. The correlation coefficient (0.092) denotes a very weak positive association, showing that changes in machine learning application have minimal influence on data processing efficiency. The coefficient of determination (r^2) = $(0.092)^2$ = 0.0085, or 0.85%, reveals that only 0.85% of the variation in data processing is explained by machine learning, while 99.15% is due to other variables. Hence, based on PV = 0.184 > 0.05 and r = 0.092, the study concludes that machine learning has no significant relationship with the processing of tax data among the 202 respondents.

Hypothesis Three

H_{o3}: Natural Language Processing (NLP) does not have a significant relationship with the collection of tax information.

H_{a3}: Natural Language Processing (NLP) has a significant relationship with the collection of tax information.

Table 10: Correlation analysis illustrating the relationship between Natural Language Processing and the collection of tax information.

Correlations			
		Natural Language	Data Collection
Natural Language	Pearson Correlation	1	.547**
	Sig. (2-tailed)		.000
	N	202	202
Data Collection	Pearson Correlation	.547**	1
	Sig. (2-tailed)	.000	
	N	202	202

**. Correlation is significant at the 0.05 level (2-tailed).

Source: SPSS Output, 2025.

Interpretation:

Table 10 presents the correlation between NLP and tax information collection. The Pearson correlation coefficient (r) is 0.547, with a p-value of 0.000. Since PV (0.000) < 0.05, the null hypothesis (H_{04}) is rejected, indicating a significant relationship between NLP and tax data collection. The correlation coefficient of 0.547 reflects a moderate positive association, implying that increased adoption of NLP enhances the efficiency of data collection. The coefficient of determination (r^2) = $(0.547)^2$ = 0.299, or 29.9%, shows that NLP explains nearly 30% of the variation in tax data collection. Consequently, the study concludes that NLP has a significant and positive effect on the collection of tax information, based on the responses of 202 participants.

Hypothesis Four

H_{05}: Natural Language Processing (NLP) does not have a significant relationship with the processing of tax information.

H_{a5}: Natural Language Processing (NLP) has a significant relationship with the processing of tax information.

Table 11: Correlation analysis depicting the relationship between Natural Language Processing and tax information processing.

Correlations			
		Natural Language	Data Processing
Natural Language	Pearson Correlation	1	.532**
	Sig. (2-tailed)		.000
	N	202	202
Data Processing	Pearson Correlation	.532**	1
	Sig. (2-tailed)	.000	
	N	202	202

**. Correlation is significant at the 0.05 level (2-tailed).

Source: SPSS Output, 2025.

Interpretation:

Table 11 shows the relationship between NLP and the processing of tax data. The correlation coefficient (r) is 0.532, with a significant value (PV) of 0.000. Since PV < 0.05, the null hypothesis (H_{05}) is rejected, confirming a significant relationship between NLP and tax data processing. The correlation coefficient of 0.532 demonstrates a moderate positive relationship, meaning that greater use of NLP tools enhances data processing accuracy and efficiency. The coefficient of determination (r^2) = $(0.532)^2$ = 0.283, or 28.3%, indicates that NLP accounts for 28.3% of the variance in data processing. Thus, the study concludes that NLP significantly and positively influences tax information processing among the 202 respondents.

Discussion of Findings

Hypothesis One: Machine Learning and Data Collection

For Hypothesis One, which examined the relationship between machine learning (ML) and tax data collection, the Pearson Product–Moment Correlation Coefficient (PPMCC) revealed a moderate positive and statistically significant correlation ($r = 0.521$, $p = 0.000$). This indicates that higher levels of ML adoption are associated with improved efficiency in tax data collection. The regression results (Model 1) corroborate this outcome, showing a significant effect of ML on data collection ($B = 0.437$, $p = 0.000$). The alternative regression estimates further support this, with an unstandardized coefficient of 0.312, a standardized Beta of 0.429, $t = 4.105$, and $p = 0.000$. Collectively, these results confirm that ML positively and significantly enhances tax data collection processes, leading to the rejection of H_{01}. These findings align with Schumpeter's Theory of Innovation, which emphasizes the role of technological advancement in improving administrative efficiency, and the Technology Acceptance Model (TAM), which states that technologies perceived as useful are more readily adopted (Raikov 2021; Bellon et al. 2022).

Hypothesis Two: Machine Learning and Data Processing

For Hypothesis Two, which assessed the effect of ML on data processing, the Pearson correlation showed a very weak and non-significant relationship ($r = 0.092$, $p = 0.184$). Similarly, Model 2 regression results ($B = 0.099$, $p = 0.186$) indicated no statistically significant predictive influence. Although an alternative regression estimation produced a significant result ($B = 0.347$, Beta = 0.462, $t = 5.022$, $p = 0.000$), the correlation analysis, which reflects the raw association, remains non-significant. Based on the correlation evidence, H_{02} is retained. This apparent divergence can be explained using TAM: perceived usefulness differs across task types, and stakeholders may view ML as more beneficial for structured activities such as data collection than for the more complex and technical procedures involved in data processing.

Hypothesis Three: Natural Language Processing and Data Collection

For tax data collection, the correlation between NLP and data collection was $r = 0.547$, $p = 0.000$, indicating a statistically significant moderate positive relationship. The coefficient of determination ($r^2 = 0.299$) suggests that 29.9% of variations in data collection are explained by NLP. Regression results show an unstandardized coefficient of 0.278, Beta = 0.387, $t = 3.432$, $p = 0.001$, confirming that a one-unit increase in NLP adoption improves data collection by 0.278 units. These findings validate the acceptance of the alternative hypothesis (H_a), demonstrating that NLP positively and moderately enhances tax data collection. This supports the Descriptive Theory, highlighting the practical application of NLP in extracting information from unstructured communications, thereby improving efficiency (Mazur 2022; Saragih et al. 2023).

Hypothesis Four: Natural Language Processing and Data Processing

For Hypothesis H_{a5}, the correlation between NLP and data processing was $r = 0.532$, $p = 0.000$, indicating a moderate positive relationship. The coefficient of determination ($r^2 = 0.283$) shows that NLP explains 28.3% of the variance in data processing. However, regression analysis reported an unstandardized coefficient of 0.126, Beta = 0.154, $t = 0.920$, $p = 0.357$, which is not significant. This suggests that while NLP is associated with processing outcomes, it does not significantly predict improvements in structured data processing, where rule-based or ML systems are more effective. This observation aligns with the theory of optimal taxation and prior studies noting NLP's strengths in handling unstructured data (Murorunkwere et al. 2022).

Conclusion

This research revealed that machine learning (ML) and natural language processing (NLP) play significant roles in enhancing various aspects of tax data management. The findings showed that ML is particularly effective in automating data collection and processing, while NLP improves the analysis of tax information, especially when dealing with unstructured data. Based on these insights, the study recommends that tax authorities adopt an integrated strategy that combines ML and NLP, supported by continuous staff training to ensure the necessary technical competencies. Implementing such a strategy would promote greater efficiency, accuracy, and innovation within tax administration.

Recommendations

Based on the objective earlier raised and the findings thereof, the following recommendations are hereby made:

Based on the conclusions drawn, this research thus advocates for the following:

i. ML should be prioritized for automating tax data collection and processing. Tax authorities can use ML algorithms for real-time data capture and classification to reduce manual work and enhance efficiency in high-volume tasks.

ii. NLP should be expanded to strengthen tax data processing, especially for interpreting unstructured text. Investing in advanced NLP tools will help authorities extract meaningful insights from documents, correspondence, and legal texts, improving analytical accuracy.

iii. Because ML performs weakly in data collection and processing, further research and development are needed. Efforts should focus on adapting ML for more complex analytical tasks through advanced cognitive AI and by integrating NLP and human expertise to support better interpretation and decision-making.

iv. ML and NLP should be integrated into a unified strategy for tax data management. Creating a centralized platform that combines ML for automation and NLP for analysis will ensure both technologies work together seamlessly and improve tax data processing across all departments.

v. Continuous training is necessary to equip tax professionals with the skills to use ML and NLP effectively. Structured programs, workshops, and hands-on sessions will help staff understand these technologies, interpret their outputs, and apply them appropriately while maintaining informed human oversight.

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