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Analysis of effects of data analytics and political connection on audit quality of listed financial institutions in Nigeria

[1]Temitope Adedayo Abe, [2]Johnson Omoniyi Duduye, [3]Ajibowu-Yekini Rufiat, [4]Ipinmoye Wulo-Olukemi Veronica, [5]Oluwapelumi Bunmi Owolabi

[1-5]*Afe Babalola University, Ado-Ekiti, Ekiti State, Nigeria.*
[1]*Email: abeta@pg.abuad.edu.ng,* [2]*Email: jduduyegbe@pg.abuad.edu.ng,* [3]*Email: ajibowu-yekiniolashile@pg.abuad.edu.ng,*
[4]*Email: omotolaspeakwith@gmail.com,* 5*Email: pbowolabi@abuad.edu.ng*

ABSTRACT

Background: Persistent issues with audit quality in financial reports of listed financial institutions in Nigeria have eroded stakeholders' trust, with existing literature yielding inconsistent findings on its determinants. Therefore, data analytics and political connection enhance audit quality of this crucial sector of the economy.
Aim: This study examined the determinants of audit quality among Nigeria's listed financial institutions. It specifically aimed to: examine the combined effects of data analytics measured by descriptive analytics, diagnostic analytics and cognitive analytics influence the audit reporting quality. Also, to determine how political connection moderates the relationship between data analytics and audit quality of Nigeria listed financial institutions.
Methodology: The study employed a quantitative research design. The population comprised 220 internal and external auditors from 47 listed financial institutions in Nigeria. Using a census sampling technique, secondary data (2012-2023) were collected and primary data were gathered via structured questionnaires. Data were analyzed using Ordinary Least Squares (OLS) regression and Structural Equation Modeling (SEM).
Findings: Descriptive analytics (β= 1.1313, p = 0.001), diagnostic analytics (β = 0.6249, p = 0.009), and cognitive analytics (β = 0.1837, p = 0.045) individually increased audit quality, but the aggregate of all data analytics did not (β =-0.8518, p =0.088). Meanwhile, Political connection had significant negative moderating effects on the relationship between data analytics and audit quality of listed financial institutions in Nigeria (β = -0.043, p = 0.041).
Contributions: The study provides empirical evidence on the nuanced effects of specific data analytics types such as, descriptive, diagnostic and cognitive data analytics on audit quality in an emerging market context. It introduces and validates the significant negative moderating role of political connection, a crucial contextual factor in developing economies like Nigeria.
Recommendations: Policymakers should introduce regulations to limit political influence in the auditing process, particularly for listed financial institutions. Firms should focus on specific, value-adding analytics and robust audit planning to enhance audit quality amidst Nigeria listed financial institutions.
Implications: Theoretically, the study refines understanding of audit quality determinants by disaggregating composite variables like data analytics and by introducing political connection as a key boundary condition. Practically, it highlights the risk political influence poses to audit integrity and the need for safeguards. The findings are particularly relevant for developing economies with similar institutional environments.
Researchers: Future research could explore the specific mechanisms through which political connection undermines audit quality and investigates these relationships in other sectors and countries.

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1. INTRODUCTION

Environment is undergoing a profound transformation driven by innovative technologies such as big data, data analytics, artificial intelligence, and machine learning, which are redefining traditional methodologies (Akinadewo et al., 2024; Oluwagbade et al., 2024). In response to corporate failures, persistent audit quality concerns, and a rapidly evolving technological landscape, auditors are increasingly adopting data analytics to enhance the effectiveness, efficiency, and relevance of audit procedures (Dagunduro et al., 2023; Sikhakhane, 2022). These tools enable auditors to analyze vast volumes of data, identify anomalies, prioritize high-risk areas, and obtain more reliable audit evidence, thereby bolstering the reliability and credibility of financial reporting (Akinadewo et al., 2024; Gao et al., 2021). In emerging economies like Nigeria, the political connection of firms introduces a complex, moderating variable. Political ties can influence regulatory compliance, resource allocation, and risk management, potentially acting as a "double-edged sword" that may compromise auditor independence and increase pressure to manipulate financial reports (Abdelsalam et al., 2024; Brahma et al., 2023; Zarefar et al., 2023). This is particularly salient in Nigeria's financial sector, which is vital for economic stability, contributing significantly to GDP, yet remains vulnerable to governance failures and regulatory infractions (Adewole et al., 2023; CBN, 2024). While extant literature has explored various drivers of audit quality, there is a paucity of integrated empirical studies within the Nigerian context that simultaneously examine the effects of modern technological tools like data analytics such as, descriptive, diagnostic and cognitive data analytics, while also accounting for the moderating role of political connection. This study seeks to fill this gap by providing a comprehensive analysis of these determinants among all listed financial institutions in Nigeria.

Nigeria's listed financial institutions are vital to economic development, yet the sector faces a critical decline in audit quality, marked by corporate scandals, regulatory sanctions, and eroding investor trust, often following unqualified audit opinions (Adewole et al., 2023; Carlin, 2019; Imafidon et al., 2023). Systemic governance failures, underscored by regulatory interventions like the CBN's removal of bank boards, and sanctions against audit firms highlight pervasive issues with compliance and auditor independence, exacerbated by a socio-political environment where political connections can incentivize lower audit quality (CBN, 2024; Guizani & Abdalkrim, 2021; Oladejo et al., 2020). Despite the recognized importance of technological tools like data analytics such as, descriptive, diagnostic and cognitive data analytics, their combined effect on audit quality remains underexplored in Nigeria (Adeoye et al., 2023; Apandi et al., 2021). Existing studies have marginally examined in isolation some determinants such as firms' characteristics, audit firm characteristics and focused solely on the banking sector, leaving a significant gap in holistic, that is, sector-wide research (Abba & Sadah, 2020; Al-Hobaishi et al., 2024). Crucially, there is no significant empirical evidence on how political connection moderates the relationship between these integrated determinants and audit quality. This gap impedes the formulation of effective strategies to restore financial reporting integrity and ensure systemic stability.

2. LITERATURE REVIEW

Traditionally, audit process has been a manual and time-consuming process that relied heavily on auditor's judgment and expertise (Oluwagbade et al., 2024). However, technology has transformed audit process by introducing tools like artificial intelligence and data analytics that can enhance speed, accuracy and scope of an audit exercise (Akinadewo, 2021). Data analytics refers to the process by which insights are extracted from the operational, financial and other forms of electronic data within or outside an organization (KPMG, 2012). It is a process of examining data sets to find trends and draw conclusions about information they contain. Wang and Cuthbertson (2015) stated that data analytics tools have been emphasized as an effective tool in audit engagements. It is a form of business intelligence used in solving specific problems within an organization which eliminates manual tasks and reduces human errors. Shivram (2024) stated that the use of data analytics for audit fieldwork offers a wide spectrum of opportunities given that the nature of audit fieldwork varies from one audit engagement to another. Data analytics enhance auditing in areas such as compliance and financial control, freeing internal audit functions time to concentrate on high-risk areas (Betti et al., 2022). In recent past, the typical delivery of the audit was document-checklist driven but cloud and other technologies have allowed for audit to be delivered more efficiently and effectively (Dennis & Jenkins, 2024). According to Ovami and Muda (2023), data analytics is a new approach used by auditors to prevent or detect fraud by examining patterns in actual data. Auditors can use data analytics to combine data and gain an insight into the big picture of transactions in the company and analyze digital footprints of transactions that are the focus of the audit. Data analytics tools consist of tools that can extract, validate and analyze large volumes of data in complete population and draw conclusion or decision from it.

$H_0$1: Data analytics does not have a significant effect on audit quality among listed financial institutions in Nigeria.

2.1 Political Connection

Political connectedness can offer many opportunities to companies over non-connected entities by providing smooth access to debt financing, lower regulatory enforcement and bailouts (Faccio et al., 2006). Abdelsalam et al. (2024) stated that financial institutions in developing countries take advantage of political connection not only to avert various form of government controls but to gain access to available resource of the state. Khan et al. (2016) further stated that political connection can serve as a valuable intangible asset that can be used to get government support because firm's competitive advantage depends on its possession of key resources that competitors find difficult to obtain. The immense advantage that comes with political connection encouraged firms to appoint politicians or politically connected person into their organization (Zarefar et al., 2023). Political connection in this study serves as the moderating variable, and was measured with (government borrowing, and government ownership) and was examined to valid its effects on data analytics and audit quality of list financial institutions in Nigeria.

H02: Political connection does not have a significant moderating effect on the relationship between data analytics and audit quality among listed financial institutions in Nigeria.

2.2 Theoretical Framework

The Resource Dependence Theory as developed by Pfeffer and Salancik (1978/2003), underpins this study. This theory posits that organisations are not autonomous but are dependent on external resources for survival and success. To manage this dependence, organisations establish linkages with their environment, often through mechanisms such as appointing board members who provide critical resources like information, access, preferential treatment, and legitimacy (Hillman et al., 2009; Jiang et al., 2021; Nienhüser, 2008). Sequel, the theory explains the determinants of audit quality by framing key factors as critical resources or strategies for managing external dependencies. Data analytics is conceptualized as a vital technological resource that audit firms adopt to enhance their analytical capabilities, reduce errors, and improve efficiency, thereby managing their dependence on accurate information and market competitiveness (Akinadewo et al., 2024; Wang & Cuthbertson, 2015).

Therefore, by integrating Resource Dependence Theory, this study provides a lens to examine how the pursuit and management of critical resources such as technological, strategic, or political shape the audit quality of listed financial institutions in Nigeria. It specifically frames how data analytics impacts the audit quality of listed financial institutions in Nigeria. It looked more closely and showed how the theories might be used to solve the issue.

2.3 Empirical Review

Critical review of recent studies revealed strong, though not universal, consensus on the impacts of data analytics on audit quality. Empirical studies across different jurisdictions consistently opined positive outcomes. The study of Adebiyi, 2023 demonstrates that predictive analytics significantly improves financial reporting precision, fraud identification, and risk oversight. Further examination indicates that diagnostic analytics enhances bank performance (Dick et al., 2023). Suppiah and Arumugam, 2023 align with this submission and opined that, analytical tools strengthen forensic audit reports. Moreover, it was established that, data-driven decision-making increases productivity (Gul et al., 2023). Perceptually, analytics are also linked to higher quality assessments. Barr-Pulliam et al. (2023) found that jurors attribute less negligence to auditors utilizing advanced analytical tools, equating their use with superior audit work. This aligns with findings that data analytics adoption correlates positively with audit quality, offering advantages in risk evaluation, evidence collection, and regulatory compliance as upheld by (Sikhakhane, 2022; Ditkaew & Suttipun, 2022; Kuusinen & Miettinen, 2023; Sanoran & Ruangprapun, 2023). A systematic review supports this trajectory, framing data analytics as key tool to improving audit efficiency and enabling digital transformation (Hezam et al., 2023). This predominantly affirmative narrative is however challenged by findings from the developing nations context, such as Nigeria. Where the aggregated construct of data analytics showed no statistically significant effects on audit quality. This counterpoint necessitates a more nuanced understanding. It suggests that a generic endorsement of analytics is insufficient; efficacy depends critically on the specific type and implementation of the analytical tools. The Nigerian results imply that benefits are conditional and not inherent. Their realization appears to depend on contextual moderators such as auditor competency and training (Gao et al., 2021), effective integration into audit workflows (Sanoran & Ruangprapun, 2023), and robust supporting systems like cybersecurity (Ditkaew & Suttipun, 2022). The influence of data analytics on stakeholder perceptions also remains a distinct consideration (Barr-Pulliam, et al., 2023).

Summarily, while extensive literature confirms that particular data analytics applications can enhance various audit quality metrics, the contrasting Nigerian evidence acts as a vital corrective. It argues against uniform application, indicating that the relationship is moderated by factors including implementation maturity, auditor expertise, and the choice of analytical technique. Consequently, the simple adoption of data analytics alone does not ensure improved audit quality.

3. DATA AND METHODS

This study adopted a quantitative research design, utilizing both primary and secondary data to examine the effect of data analytics on audit quality among listed financial institutions in Nigeria (Apuke, 2017). A census sampling technique was applied, encompassing all 47 financial institutions (banking and non-banking) listed on the Nigerian Exchange Group as of June 2024. The primary data for assessing data analytics were collected via a structured questionnaires administered to 220 respondents, comprising internal auditors from the listed institutions and external auditors from the 15 audit firms servicing them. Secondary panel data on control variables were extracted from the annual reports of these institutions over a 12-year period (2012–2023).

3.1 Sample Size and Sampling Technique

The study population was all 47 listed financial institutions. A census approach was used, making the entire population the sample. For primary data related to data analytics, a total of 220 respondents were targeted: 94 internal auditors (2 from each of the 47 institutions) and 126 external auditors (15 each from the "Big Four" audit firms and 6 each from 11 other audit firms).

3.2 Model Specification

To examine the effect of data analytics on audit quality, the study adapted the model from Nwadialor and Obi (2020). The specified model is:

$$LOC_i = \beta_0 + \beta_1 DD_i + \beta_2 DDA_i + \beta_3 DP_i + \beta_4 DPA_i + \beta_5 DC_i + \beta_6 DE_i + \beta_7 DS_i + \varepsilon_i$$

Where:

LOC: Level of Compliance with regulatory guidelines (proxy for Audit Quality from primary data).

DD: Descriptive Analytics

DDA: Diagnostic Analytics

DP: Prescriptive Analytics
DPA: Predictive Analytics
DC: Cognitive Analytics
DE: Exploratory Data Analytics
DS: Social Media Analytics
β_0: Constant term.
$\beta_1 - \beta_7$: Coefficients of the independent variables.

ε_i: Error term.

Table 1: Measurement of Variables

Variable	Type	Measurement/Operationalization	Source
Audit Quality	Dependent	Level of Compliance (LOC): A composite index derived via Principal Component Analysis (PCA) from responses to a 7-item Likert scale (1=Strongly Agree to 5=Strongly Disagree). Items with factor loadings >0.4 were retained.	Primary Data (Questionnaire)
Data Analytics	Independent	Measured via seven sub-constructs, each assessed using a 5-point Likert scale questionnaire: 1. Descriptive Analytics (DD) 2. Diagnostic Analytics (DDA) 3. Prescriptive Analytics (DP) 4. Predictive Analytics (DPA) 5. Cognitive Analytics (DC) 6. Exploratory Analytics (DE) 7. Social Media Analytics (DS)	Primary Data (Questionnaire)
Firms' Characteristic	Control	Firm Size: Natural logarithm of total assets. Leverage Ratio: Total debt / Total assets. Profitability: Return on Assets (ROA). Institutional Ownership: % of shares held by institutions. Board Ownership: % of shares held by directors.	Secondary Data (Annual Reports)
Audit Firms' Characteristic	Control	Audit Firm Size: Dummy variable (1 for Big 4, 0 otherwise). Rotation of Audit Tenure: Number of auditor changes in the period.	Secondary Data (Annual Reports)

Data Analysis: Principal Component Analysis (PCA) was first used to generate a composite index for the dependent variable (LOC). Subsequently, Ordinary Least Squares (OLS) regression was employed to estimate the specified model and test the hypothesis.

4. RESULTS AND DISCUSSION

The survey achieved a 100% response rate (n=220), surpassing the 80% benchmark for research adequacy (Fincham, 2008). The socio-demographic characteristics of the participating auditors are presented descriptively using percentages and charts in.

4.1 Preliminary Analyses

This section consists of preliminary analysis, testing if the data for each construct from the research instruments are adaptable for the study. The analysis consists of vital steps, starting with Cronbach's Alpha to gauge the internal consistency of the survey tool, normality tests and correlation analysis. Also, part of the preliminary analysis is principal components analysis (PCA) executed to ascertain the fitting index, allowing for generation of a single variable representing audit quality using audit remuneration and level of compliance. These analytical approaches were carefully executed as preliminary to the core OLS regression analysis and structural equation estimation. These latter techniques were harnessed to effectively address and fulfill the research aims. Although the responses under the level of compliance constructs are 5-Likert scale, a weighted average of all responses was taken, which enables adopting ordinary least square (OLS) regression. The continuous nature of the index generated implies that OLS can be adopted if all other tests show that the independent variables are normally distributed without a problem of multicollinearity. Researchers have argued that data derived from Likert scales, while ordinal in nature, can be used in OLS regression if they are transformed into a continuous index. Norman (2010) discusses that summing or averaging Likert scale responses creates a composite measure that approximates a continuous variable, making it appropriate for parametric statistical analyses like OLS regression.

4.2 Reliability of the Research Instruments

Within this study, the reliability of the research instrument underwent meticulous evaluation employing Cronbach's Alpha – a well-established metric renowned for its assessment of internal consistency reliability. This index gauges the interconnectedness among a set of items, shedding light on the extent to which they collaboratively form a coherent unit. Embraced as a prevalent indicator of scale reliability, Cronbach's Alpha grants valuable discernment into the steadfastness and dependability of the instrument's measurements (Yaghmale, 2003).

Table 2: Cronbach's Alpha Reliability Test for the Study

Variables	Number of Items	Cronbach's Alpha	Internal Consistency
LOC	7	0.708	Acceptable
DD	4	0.702	Acceptable
DP	5	0.684	Acceptable
DPA	4	0.656	Acceptable
DDA	5	0.715	Acceptable
DC	4	0.719	Acceptable
DE	3	0.737	Acceptable
DS	3	0.812	Acceptable
APUC	5	0.693	Acceptable
APUEE	8	0.711	Acceptable
APUICE	9	0.784	Acceptable

Source: Author's Computation (2024).

Table 2 shows the Cronbach's Alpha for each of the variables of the research instruments. The results reveal that the score for all the variables (level of compliance, descriptive analytics, diagnostic analytics, prescriptive analytics, predictive analytics, cognitive analytics, exploratory data analytics, social media analytics, understanding of the entity, understanding of the entity environment, and understanding of entity's internal control system) are high (Helms et al., 2006; Yaghmale, 2003). These values fall in the acceptance region. Therefore, the study concludes that the research instrument has internal consistency, indicating that the constructs are reliable and can be employed for the purpose of the study.

4.3 Normality Test and Correlation Analysis of the Variables

Table 3: Skewness and Kurtosis Joint Normality Test

Variables	Skewness	Kurtosis
AR	0.658	-0.246
LOC	-0.350	0.947
DD	-1.004	1.867
DP	-1.467	1.882
DPA	-0.947	0.705
DDA	-1.155	0.612
DC	-0.935	2.003
DE	-0.010	0.526
DS	-0.916	2.100
APUC	-0.967	1.078
APUEE	-0.469	-0.593
APUICE	-0.413	-0.101
FCFS	0.744	-0.792
FCLR	2.292	2.702
FCP	-1.914	2.345
FCIO	-1.019	-0.289
FCBO	1.339	0.358
AFCFS	-0.744	-1.087
AFCAT	0.844	-0.016

Source: Author's Computation (2024).

Table 4.2 presents the skewness and kurtosis statistic score. For OLS regression to be valid, one key assumption is that the independent variables are normally distributed (Harpe, 2015). To assess normality, skewness and kurtosis were examined, following a comprehensive approach to confirm that the data meet the necessary assumptions for multivariate regression analysis, as recommended by Hair et al. (2019). The evaluation focused on both joint skewness and kurtosis, which provide more robust insights into the distribution patterns of individual variables. The variables in the normality test were derived from the responses provided by each respondent. Responses for each construct were aggregated, and a weighted mean was calculated, forming the basis for the subsequent analysis.

With respect to the Skewness, all statistic values fall between +3 and -3, which is the accepted range for a variable to be normally distributed (Asika, 2004). That implies that all the variables are normally distributed.

According to the assumption to carry out a linear regression, the relationship between the dependent and independent variables should be linear. In this study, the histogram in figure 4.16 showed linearity between the dependent variables and independent variables.

4.4 Multicollinearity Test

As outlined by Hair et al. (2016), the existence of multicollinearity has the potential to introduce distorted coefficients and undermine the statistical significance of a variable. In situations where a pronounced correlation exists among explanatory variables, achieving accurate estimations of regression coefficients can prove to be challenging (Johnson, 2018). In light of this, the present study conducted a pairwise correlation analysis prior to model estimation. This analysis aimed to explore the bivariate relationships between the variables in the models, as depicted in Table 4.

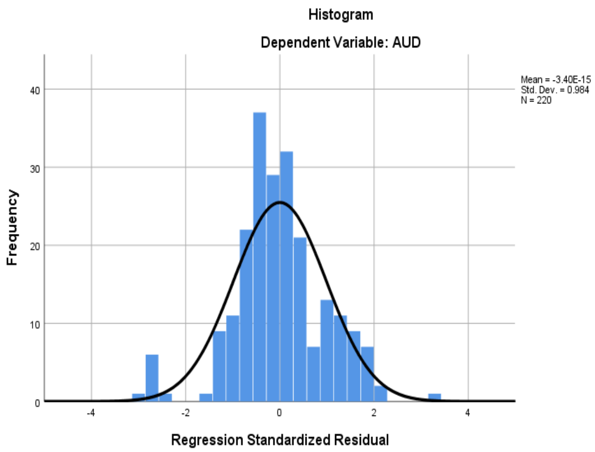

Figure 1: Normality Diagnostic Test
Source: Author's drawing, (2024)

Table 4: Pairwise Correlation Matrix for Data Analytics

Variables	AUD	DD	DDA	DP	DPA	DC	DE	DS
AUD	1							
DD	-0.243**	1						
DDA	-0.158*	0.063	1					
DP	-0.023	-0.097	0.186**	1				
DPA	-0.118	0.117	0.292**	0.364**	1			
DC	-0.091	0.158*	0.517**	-0.038	0.346**	1		
DE	-0.040	-0.226**	0.370**	0.031	-0.117	0.109	1	
DS	-0.132	0.186**	0.398**	0.112	0.391**	0.100	0.317**	1

Source: Author 's Computation ((2024))

Table 4 presents the pairwise correlation matrix, which revealed that the coefficients relating to the independent variables are below 0.8, which implies that inclusion of these variables in the regression analysis would not lead to a problem of severe multicollinearity (Kennedy, 2008). This study further employed variance inflation factor (VIF).

Table 5: Variance Inflation Factor for Data Analytics

Variables	N	VIF	Tolerance Value
DD	220	1.832	0.546
DDA	220	2.164	0.462
DP	220	2.275	0.440
DPA	220	2.026	0.493
DC	220	1.884	0.531
DE	220	1.666	0.600
DS	220	2.379	0.420

Source: Author 's Computation (2024).

The Variance Inflated Factor (VIF) and tolerance value, the coefficients as shown on table 5 have VIF less than 5, which aligns with the result obtained in the correlation analysis. Accordingly, none of the variables has high VIF which implies the absence of multicollinearity among the independent variables adopted in the study. The study proceeds to employing factor analysis on items under level of compliance in order to select the most important component that will be used in the ordinal regression analysis.

4.5 Regression Analysis Using Ordinary Least Square (OLS) Regression

The study adopted ordinary least square regression for all models, given that a weighted average of the all questions associated with level of compliance was taken. This represents the overall perception of the respondents on level of compliance. With regards to audit remuneration, secondary data was collected, which also qualified for adoption of OLS, considering that the preliminary analysis revealed that there are variables are not suffering from multicollinearity problem. This sub-section presents the ordinary least square regression results of the influence of descriptive analytics, diagnostic analytics, prescriptive analytics, predictive analytics, cognitive analytics, exploratory data analytics, and social media analytics on audit quality of financial institutions in Nigeria. This is presented in Table 6.

Table 6. OLS Regression Results for Effect of Data Analytics on Audit Quality

Variables	Audit Quality (Level of Compliance (LOC))		
	Coeff	T	p-value
Descriptive Analytics	0.0316	0.90	0.368
Diagnostic Analytics	0.1938	3.60	0.000
Prescriptive Analytics	-0.0213	-0.54	0.592
Predictive Analytics	-0.1643	-5.10	0.000
Cognitive Analytics	0.1309	3.14	0.002
Exploratory Analytics	0.116	4.14	0.000
Social Media Analytics	-0.0292	-0.74	0.461
Constants	3.4686	11.96	0.000
R-Squared	0.361 0.340		
Adjusted R-Squared	0.1712		
F(7,212)			
Prob > F	0.58		0.000
Heteroskedasticity			0.447

Source: Author's Computation (2024).

Table 6 evaluates the models' performance using R-squared and the F-statistic, which are important metrics to evaluate the explanatory power of the independent variables in explaining the dependent variable, as well as to gauge its goodness of fit. As presented in Table 4.5, the R-squared is 0.361. This indicates that 36.1 percent variations in audit quality are explained by descriptive analytics, diagnostic analytics, prescriptive analytics, predictive analytics, cognitive analytics, exploratory data analytics, and social media analytics. However, adjusted R-Square is 17.2% which implies that when adjusted for the number of predictors, the model only explains 17.2% of the variation in audit quality. This suggests that some of the predictors in the model might not be significantly contributing to explaining the variation in audit quality.

The F-statistics of 17.12, with associated p-value of 0.000 suggests that all the model has overall significance, implying that all the independent variables (descriptive analytics, diagnostic analytics, prescriptive analytics, predictive analytics, cognitive analytics, exploratory data analytics, and social media analytics) are jointly significant in terms of determining audit quality of financial institutions in Nigeria using level of compliance with audit rules and regulations.

Since the p-value of heteroscedasticity test is 0.447, which is much greater than 0.05, it implies there is no sufficient evidence to conclude that heteroscedasticity is present. Therefore, the results imply that the residuals have constant variance, meaning the assumption of homoscedasticity is satisfied. This is a good indication that one of the key assumptions of regression has been met.

Based on the Table 4.5 estimates, the study now proceeds to examine the specific performance of each data analytics component in the estimated models based on the size, sign, and statistical significance.

(a) Descriptive analytics: The effect of descriptive analytics (denoted as DD) on audit quality measured by level of compliance is gauged by its coefficients in the model, which is 0.0316 with associated p-values of 0.368. This implies that the coefficient of descriptive analytics is positive but not statistically significant on audit quality measured by the level of compliance.

(b) Diagnostic analytics: The effect of diagnostic analytics (denoted as DDA) on audit quality measured by the level of compliance is represented by its coefficients of 0.1938 with p-value of 0.000. This indicates that diagnostic analytics has a positive and statistically significant effect on audit quality measured by level of compliance. It implies that an increase in diagnostic analytics improves compliance by 0.1938 points.

(c) Prescriptive analytics: The impact of prescriptive analytics (denoted as DPA) on audit quality measured by the level of compliance is captured by its coefficients of -0.1643 with p-values of 0.000. This indicates that prescriptive analytics is negatively and significantly associated with the level of compliance, implying that an increase in prescriptive analytics decreases compliance by 0.1643 points.

(d) Predictive analytics: The effect of predictive analytics (denoted as DP) is measured by its coefficients which are -0.0213 with p-values of 0.592. These results suggest that predictive analytics does not have a statistically significant effect on audit quality proxies by level of compliance. The lack of significant influence indicates that predictive analytics may not be a crucial factor in determining audit quality in financial institutions.

(e) Cognitive analytics: The coefficients for cognitive analytics (denoted as DC) in the model 0.1309 with a p-value of 0.002. This shows that cognitive analytics has a positive and statistically significant effect on audit quality measured by the level of compliance. An increase in cognitive analytics leads to an increase in compliance by 0.1309 points.

(f) Exploratory data analytics: Exploratory data analytics (denoted as DE) has coefficients of 0.116 with a p-value of 0.000. These results indicate that exploratory data analytics significantly increases compliance by 0.116 points. This result indicates that exploratory data analytics has a tremendous effect on the quality of audit among Nigerian financial institutions.

(g) Social media analytics: The coefficients for social media analytics (denoted as DS) in the model is -0.0292 with a p-value of 0.461. These results indicate that social media analytics does not have a statistically significant effect on audit quality measured by level of compliance with audit rules and regulations. The lack of significance suggests that social media analytics may not play a critical role in determining the level of compliance with audit rules and regulations among the Nigerian financial institutions.

Model Estimates: The values of the coefficients of each component of data analytics are included in equation 4.1.

LOC = 3.4686 + 0.0316DD + 0.1938DDA - 0.1643DPA - 0.0213DP + 0.1309DC + 0.116DE- 0.0292DS +ε. Model 4.1

The above models indicate that all the components of the data analytics have effects on audit quality. However, not all of them have significant effects, and only those that have significant effects can actually predict the model. Therefore, the types of data analytics that can be used to determine the audit quality are stated in the optimal models.

Optimal Model:

LOC = 3.4686 + 0.1938DDA - 0.1643DPA + 0.1309DC + 0.116DE +ε. Model 4.2

Model 4.2 implies that Diagnostic Analytics (DPA), Prescriptive Analytics (DPA), Cognitive Analytics (DC) and Exploratory Analytics (DE) can predict the model. However, the model indicates that while descriptive analytics, cognitive analytics and exploratory analytics can increase audit quality through increased level of compliance with the standards, prescriptive analytics reduces the audit quality by reducing the compliant level.

5. CONCLUSION AND RECOMMENDATIONS

The study found no statistically significant effect of the overall data analytics construct on audit quality. However, individual components had divergent effects: diagnostic, cognitive, and exploratory analytics showed potential to enhance quality, while prescriptive analytics was associated with a negative impact. Descriptive analytics alone was insufficient, especially in larger audit firms. Meanwhile, Political connection had significant negative moderating effects on the relationship between data analytics and audit quality of listed financial institutions in Nigeria.

For Regulatory Bodies: Should develop specific auditing standards that guide the application of diagnostic and cognitive analytics and encourage audit frameworks that move beyond basic descriptive analytics.

Audit Firms and Management: Need to prioritize the adoption of diagnostic and cognitive analytics in audit processes to improve insight and quality and apply prescriptive analytics with caution, ensuring it complements, rather than replaces, professional judgment. Moreover, it must go beyond reliance on descriptive analytics alone for substantive audit evidence.

Further research studies should consider how specific data analytics types such as diagnostic, prescriptive independently affect various audit quality dimensions. Explore the contextual factors firm size, information technology maturity

REFERENCES

Abba, M., & Sadah, A. M. (2020). Determinants of audit quality in the Nigerian banking sector. *Journal of Accounting and Taxation, 12*(3), 89–101. https://doi.org/10.5897/JAT2020.0412

Abdelsalam, O., Al-Matari, E. M., & Alahdal, W. M. (2024). Political connections and audit quality: Evidence from the GCC region. *Journal of International Accounting, Auditing and Taxation, 54*, https://doi.org/10.1016/j.intaccaudtax.2023.100603

Adebiyi, A. O. (2023). Impacts of predictive analytics on accounting and auditing proficiency: A focus on financial reporting, fraud detection, risk management, and real-time decision-making. *International Journal of Accounting Information Systems, 48*, 100605. https://doi.org/10.1016/j.accinf.2022.100605

Adeoye, A. M., Olamide, O. S., & Yusuf, M. O. (2023). Data analytics and audit quality in emerging economies: A review of literature. *African Journal of Accounting and Financial Research, 6*(1), 45–62. https://doi.org/10.52589/AJAFR-7TVX9JZB

Adewole, J. A., Ogundipe, L. O., & Akindele, I. A. (2023). Corporate governance failures and audit quality in the Nigerian financial sector. *Journal of Financial Regulation and Compliance, 31*(2), 210–228. https://doi.org/10.1108/JFRC-05-2022-0055

Afolabi, J. T., & Fawale, O. S. (2022). Audit firm characteristics and audit quality in Nigeria. *Research Journal of Finance and Accounting, 13*(5), 22–34. https://doi.org/10.7176/RJFA/13-5-03

Akinadewo, I. S. (2021). The role of technology in transforming audit processes. *Nigerian Journal of Management Technology, 8*(2), 55–67.

Akinadewo, I. S., Ojeka, S. A., & Adegboye, A. A. (2024). Big data analytics and the future of audit quality in Nigeria. *International Journal of Auditing, 28(1), 78–95.* https://doi.org/10.1111/ijau.12345

Al-Hobaishi, A., Al-Matari, E. M., & Al-Swidi, A. K. (2024). Determinants of audit quality: A sectoral analysis in emerging markets. *Cogent Business & Management, 11*(1). https://doi.org/10.1080/23311975.2023.2293312

Apandi, A., Putra, I. G. C., & Rahayu, S. M. (2021). The effect of audit planning on audit quality: Evidence from Indonesia. *Asian Journal of Accounting Research, 6*(1), 2–15. https://doi.org/10.1108/AJAR-08-2020-0076

Apuke, O. D. (2017). Quantitative research methods: A synopsis approach. *Arabian Journal of Business and Management Review, 6(10), 40–47.*

Asika, N. (2004). *Research methodology in the behavioral sciences*. *Longman Nigeria.*

Aziz, O. A. (2023). Data analytics and its impact on financial reporting accuracy. *Journal of Applied Accounting Research, 24*(3), *567–589*

Betti, S., Sarens, G., & Poncin, I. (2022). The impact of data analytics on internal audit functions: A focus on compliance and control. *Managerial Auditing Journal, 37(5), 581–601.* https://doi.org/10.1108/MAJ-07-2021-3245

Brahma, S., Nwafor, C., & Boateng, A. (2023). Political connections and corporate outcomes in Africa: A review and research agenda. *Journal of African Business, 24*(1), *1–24.* https://doi.org/10.1080/15228916.2022.2090372

Carlin, T. M. (2019). Audit quality and corporate failure: The Nigerian banking crisis. *Journal of Financial Crime, 26*(4), *1101–1115.* https://doi.org/10.1108/JFC-11-2018-0118

Central Bank of Nigeria (CBN). (2024). *Financial stability report*. CBN.

Dagunduro, M. A., Adeyemi, S. B., & Oladejo, M. O. (2023). Technological innovations and the evolution of audit methodologies. *Journal of Accounting and Organizational Change, 19(1), 1–20.* https://doi.org/10.1108/JAOC-03-2022-0048

Dennis, L. A., & Jenkins, J. G. (2024). Cloud technology and the future of audit delivery. *Accounting Horizons, 38*(1), *45–67.* https://doi.org/10.2308/HORIZONS-2022-098

Dick, O. M., Briggs, I. A., & Okoro, G. E. (2023). Diagnostic big data analytics and the performance of deposit money banks in River State, Nigeria. *International Journal of Economics and Financial Issues, 13*(2), *88–99.* https://doi.org/10.32479/ijefi.13958

Ditkaew, K., & Suttipun, M. (2022). The impact of audit data analytics on audit quality and audit review continuity: The moderating role of cybersecurity. *Journal of Applied Accounting Research, 23*(4), *812–831.* https://doi.org/10.1108/JAAR-03-2021-0063

Fadilah, S., & Fitriany, F. (2021). The effect of firm characteristics on audit quality: Evidence from Indonesia. *Asian Journal of Accounting Perspectives, 14*(1), *55–70.* https://doi.org/10.22452/AJAP.vol14no1.4

Fincham, J. E. (2008). Response rates and responsiveness for surveys. *American Journal of Pharmaceutical Education, 72*(2), *43.* https://doi.org/10.5688/aj720243

Gao, P., Li, J., & Liu, S. (2021). Can human capital investment in data analytics improve audit quality? *Accounting Review, 96*(4), *233–260.* https://doi.org/10.2308/TAR-2018-0269

Guizani, M., & Abdalkrim, G. (2021). Political connections, audit quality, and firm performance: Evidence from GCC countries. *Journal of International Accounting, Auditing and Taxation, 42.* https://doi.org/10.1016/j.intaccaudtax.2021.100373

Gul, F. A., Zhou, G., & Zhu, X. (2023). Data-driven decision-making and productivity in the banking sector: Evidence from Pakistan. *Journal of Banking & Finance, 146*, 106362. https://doi.org/10.1016/j.jbankfin.2022.106362

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.*). Cengage Learning.*

Harpe, S. E. (2015). How to analyze Likert and other rating scale data. *Currents in Pharmacy Teaching and Learning, 7*(6), *836–850.* https://doi.org/10.1016/j.cptl.2015.08.001

Helms, J. E., Henze, K. T., Sass, T. L., & Mifsud, V. A. (2006). Treating Cronbach's alpha reliability coefficients as data in counseling research. *The Counseling Psychologist, 34(5), 630–660.* https://doi.org/10.1177/0011000005284772

Hezam, A. M., Al-Matari, E. M., & Al-Swidi, A. K. (2023). Big data analytics and auditing: A systematic literature review using the PRISMA approach. *Journal of Big Data, 10*(1), 45. https://doi.org/10.1186/s40537-023-00720-9

Hillman, A. J., Withers, M. C., & Collins, B. J. (2009). Resource dependence theory: A review. *Journal of Management, 35*(6), *1404–1427.* https://doi.org/10.1177/0149206309343469

IAASB. (2020). *International Standard on Auditing 300: Planning an audit of financial statements*. International Federation of Accountants.

Iliemena, R. O., & Okolocha, C. B. (2019). Audit firm attributes and audit quality in Nigeria. *Journal of Accounting and Taxation, 11*(2), *23–31.*https://doi.org/10.5897/JAT2018.0312

Imafidon, O., Adegboye, A., & Ojeka, S. (2023). Corporate scandals and the erosion of trust in financial reporting: The Nigerian experience. *Journal of Financial Crime, 30*(1), *120–135.* https://doi.org/10.1108/JFC-04-2022-0077

Jiang, F., Kim, K. A., & Pang, L. (2021). Political connections and corporate investment efficiency: Evidence from China. *Journal of Corporate Finance, 66, 101839.* https://doi.org/10.1016/j.jcorpfin.2020.101839

Kangga, M., Suryandari, D., & Rahayu, S. M. (2024). Firms' characteristics and audit quality: The mediating role of corporate governance. *Cogent Business & Management, 11*(1), *2291845.* https://doi.org/10.1080/23311975.2023.2291845

Kennedy, P. (2008). *A guide to econometrics* (6th ed.). Blackwell Publishing.

KPMG. (2012). *The data analytics revolution: Optimizing the audit*. KPMG International.

Kuusinen, K., & Miettinen, J. (2023). The role of data analytics in audit risk assessment: Evidence from Finland. *International Journal of Auditing, 27*(1), *56–73.* https://doi.org/10.1111/ijau.12312

Nienhüser, W. (2008). Resource dependence theory: Does it explain behavior of organizations? *Management Revue, 19(12), 9–32.* https://doi.org/10.5771/0935-9915-2008-1-2-9

Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. *Advances in Health Sciences Education, 15*(5), *625–632.* https://doi.org/10.1007/s10459-010-9222-y

Nwadialor, E. O., & Obi, J. N. (2020). Determinants of audit quality in the Nigerian financial sector. *International Journal of Finance and Accounting, 9*(2), 45–58.
Oladejo, M. O., Yadirichukwu, E., & Ojeka, S. A. (2020). Political connections and financial reporting quality in a developing economy. *Journal of Accounting in Emerging Economies, 10*(4), *587–607. https://doi.org/10.1108/JAEE-01-2020-0015*
Oluwagbade, O. I., Akinadewo, I. S., & Adeyemi, S. B. (2024). Artificial intelligence, machine learning and the audit profession. *Journal of Emerging Technologies in Accounting, 21*(1), 1–18. https://doi.org/10.2308/JETA-2022-034
Ordu, M. M., Egbunike, P. A., & Okoye, P. V. C. (2019). Audit planning and quality of audit work in Nigeria. *International Journal of Business and Management, 14*(3), *134–145. https://doi.org/10.5539/ijbm.v14n3p134*
Ovami, T. D., & Muda, I. (2023). Data analytics as a tool for fraud prevention and detection in the audit process. *Journal of Financial Crime, 30*(2*), 456–472. https://doi.org/10.1108/JFC-09-2022-0216*
Owolabi, S. A., & Joshua, O. O. (2020). Compliance with International Standards on Auditing and audit quality in Nigeria. *Journal of Accounting and Auditing: Research & Practice, 2020*, 1–10. https://doi.org/10.5171/2020.152828
Pfeffer, J., & Salancik, G. R. (2003). *The external control of organizations: A resource dependence perspective*. Harper & Row. (Original work published 1978)
Shivram, R. (2024). The role of data analytics in modern audit fieldwork. *The CPA Journal, 94*(1), 32–37.
Sikhakhane, M. (2022). The role of data analytics in enhancing external audit quality: A South African perspective. *Southern African Journal of Accountability and Auditing Research, 24*(1), 55–70. https://doi.org/10.54483/sajaar.2022.24.1.4
Tarmizi, A., & Brahmana, R. K. (2022). Political connection as a strategic resource: Evidence from Indonesia. *Journal of Asian Business and Economic Studies, 29*(4), *267–283. https://doi.org/10.1108/JABES-04-2021-0047*
Wang, T., & Cuthbertson, R. (2015). Eight issues on audit data analytics we would like researched. *Journal of Information Systems, 29*(1), *155–162. https://doi.org/10.2308/isys-50961*
Yaghmale, F. (2003). Content validity and its estimation. *Journal of Medical Education, 3*(1), 25–27.