Audit Report Lag Responsiveness of Text Data Analytics: Time-Saving or Time-Demanding? Evidence from Nigeria

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DOI: https://doi.org/10.51244/IJRSI.2026.1306000236

Received: 10 June 2026; Accepted: 15 June 2026; Published: 02 July 2026

ABSTRACT

In response to concerns about existential threat of the audit profession that followed the emergence of artificial intelligence (AI), the current study was undertaken to investigate the potential complementary role of the technology in solidifying the profession through its deployability on text data analytics. Against this backdrop, the study investigated the impact of text data analytics on audit report lag of listed manufacturing firms in Nigeria. A mixed method design was implemented wherein primary data were sourced from the external auditors at firm-level to measure text data analytics, while secondary data were collected from the audited annual reports of the manufacturing firms. Following analyses, it was found that text data analytics associated positively with audit report lag elongation. Consequently, it was conclusive that text data analytics has the potential to contribute to audit quality through enablement of professional skepticism. It was therefore recommended, among others, that regulatory bodies such as Financial Reporting Council of Nigeria should promote the use of text data analytics in auditing through guidelines, standards, or incentives.

Key Words: Text Data Analytics, Audit Report Lag, Nigeria

INTRODUCTION

Emergence of artificial intelligence (AI) is eliciting doubts and anxiety about the continued relevance of auditing profession. In response to the alleged threat, several scholars have argued that the emergence of AI has created more opportunities than threats (e.g. Brynjolfsson, & McAfee, 2014; Davenport, & Dyché, 2013; and Agrawal, Gans, & Goldfarb, 2018). One of such argument is that, the deployability of AI in conjunction with availability of big data, presents compelling recipe for evidence gathering in auditing, through big data analytics, (Oyeniyi, Ugochukwu, Mhlongo, 2024; and Alles & Gray, 2016). In fact, the utilisation of big data analytics (BDA) in audit methods has been adopted by external auditors in response to the prevalence of big data environment (Bonsu, Roni, & Guo, 2023). This technology enables the comprehensive transformation of unstructured data from clients or third-party sources into useful and meaningful insights. BDA has become regarded as one of the foundational technologies that have the potential and ability to provide businesses with significant economic value. The technology has increasingly emerged as a crucial component and frontier of chance for auditors to improve their professional effectiveness (Yadegari-dehkordi *et al*., 2019). In audit literature, one crucial yardstick for measuring audit effectiveness is audit report timeliness.

Timely dissemination of audited reports increases the relevance of information, trustworthiness, dependability, and knowledge of corporate actions (Chalu, 2021). For Blankley Hurtt, and MacGregor (2014), the postponements in issuing an audit report raise information asymmetry and ambiguity. Delays may jeopardize the businesses' independence and responsibility that are critical for enticing shareholders to make an investment decision. Therefore, the subject of Audit Report Lag (ARL) is significant since it is connected to corporate transparency and serves as a good indication for outsiders to judge the efficiency of external audits. As a key aspect in defining the quality of financial information, scholars have alluded to a number of measures that are aimed at shortening ARL (Krahel, & Titera, 2015; Dai, & Vasarhelyi, 2016; and Chen, & Wang, 2017). One of such measures is text data analytics.

As one of the three forms of BDA, text data analytics (TDA) appears to be the most popular in the audit industry (Henry, Holtzman, Rosenthal, & Weitz, 2023). The popularity might not be unconnected with the propagation of the 'audit latency reduction' gospel, championed by scholars such as Anantharaman, (2018), Rezaee, Mora and Homayoun (2017), Brown-Liburd and Vasarhelyi (2015), and Krahel and Titera (2015). For instance, Rezaee, *et al* (2017) assert that the utilization of text data will influence audit latency by streamlining data acquisition and management to facilitate audit analytical review and enhance client business intelligence. For Anantharaman (2018), Brown-Liburd, and Vasarhelyi, (2015), the authors suggested that text analytics can improve audit efficiency and reduce audit latency.

However, strands of scholars argue that positive ARL response coefficient of TDA serves as empirical rebuttal against the avowed complementary role of TDA, (Berton, 2017; Janvrin, & Bierstaker, 2016; Krahel, & Titera, 2015; and Wang, & Tuttle, 2017). In other words, such studies provide evidence that the use of data analytics in auditing can lead to elongated audit report lag, contrary to the expected benefits of improved efficiency and accuracy. In faulting TDA as panacea to audit quality due to its tendency to elongate ARL, the role of professional skepticism as audit quality-enhancing mechanism is often overlooked.

One of the influencing factors of professional skepticism is auditors' competence (Razana, Tarmizi & Sayed, 2022). Deficiency in auditors' expertise may impede the appropriate use of professional skepticism. Auditors with decent and respectable knowledge and experience tend to be more skeptical when making judgements and decisions, (Razan, *et. al*., 2022). The more competent an auditor is, the more he or she can evaluate the proficiency level of evidence with more in-depth and well-defined capability. In the context of the current study, competency here denotes technical capability (i.e., possession of TDA skill), hence establishing TDA as stimulant of audit report lag. In this way, leveraging on the premise that TDA as a technology serves as launchpad for auditors to immerse deeper into professional skepticism, leading to expansion of the evidence gathering scope of auditors, a positive relationship can be inferred between TDA and audit report lag.

Therefore, contrary to the general postulations that TDA reduces ARL, adoption of the technology is likely to result in ARL reduction (i.e. confirmation of the 'efficiency' argument) or elongation (i.e. confirmation of the 'professional skepticism' argument). An ARL response coefficient of TDA if negative, it implies supremacy of 'efficiency' argument over 'professional skepticism' argument. On the other hand, if the coefficient is positive, it would mean that 'professional skepticism' argument prevails over the 'efficiency' argument. Either outcome still accentuates the significance of AI in auditing, proving that its emergence has created more opportunities for the continued relevance of the accounting profession.

Studies on ARL in Nigeria has been done extensively (e.g. Nwaimo, Adegbola, Adegbola, & Adeusi, 2024; Adeyemi & Olowookere, 2015; Akani, 2017; Ezugwu & Ezejiofor, 2018; Ogundele & Bello, 2015 and Uadiale, 2016). However, studies on the nexus between TDA and ARL is not only scanty, to the best of the authors' knowledge, such study in Nigerian context is non-existent. Consequently, empirical validation on the presumed relationship between ARL and TDA cannot be ascertained with certainty. In fact, the only study that comes close to exploring the link between TDA and ARL is that by Nwadialo and Obi (2020) who examined the effect of big data on the quality of audit reports in Nigeria's Anambra State, wherein result confirmed big data as having positive effect on audit timeliness. While Nwadialo's and Obi's (2020) study has highlighted positive link between big data and audit timeliness, the study failed to disaggregate big data into its various constituents. Consequently, the effect of text data analytics on audit timeliness in Nigeria still remains largely unknown. In this paper, we contribute to knowledge by improving upon the insights provided by Nwadialor and Obi (2020) to link TDA and ARL, drawing evidence from listed manufacturing firms in Nigeria.

The remainder of this paper is structured as follows. Section 2 describes the theoretical framework and relevant literature on the main study variables. The methodology employed in the study is presented in section 3. The research findings are presented in Section 4 while Section 5 outlines the study's conclusion.

LITERATURE REVIEW

Theoretical Foundation

Policeman Theory

The Policeman Theory, initially proposed by Charles F. Hickson in the early 20th century, suggests that auditors act as vigilant overseers, detecting and deterring financial irregularities, fraud, and misstatements in financial reporting (Hayes, Dassen, & Schilder, 1999). This theory underscores the crucial role auditors play in maintaining the integrity of financial information, which is vital for the functioning of capital markets and the trust of various stakeholders. The Policeman Theory, also known as the "watchdog theory," posits that auditors act as the guardians or policemen of financial systems, entrusted with the responsibility of detecting and preventing financial misconduct, fraud, and errors. This theory accentuates the auditor's role as an independent and objective evaluator, ensuring that financial statements present a true and fair view of an organization's financial position. It places auditors in the position of vigilantly overseeing financial operations, acting as a safeguard against financial improprieties (Humphrey *et al*.,1993).

In the context of text data analytics, the policeman theory of audit might explain a positive relationship between text data analytics and audit report lag. With the use of text data analytics, auditors may become more meticulous in their examination of financial statements and related documentation. This increased scrutiny could lead to a more thorough and time-consuming audit process, resulting in longer audit report lag. Furthermore, text data analytics enables auditors to analyze large volumes of unstructured data, such as emails, contracts, and meeting minutes. This more detailed analysis could uncover additional issues or anomalies that require further investigation, leading to increased audit report lag. By considering these factors, the policeman theory of audit provides a framework for understanding how the use of text data analytics might lead to a positive relationship with audit report lag.

Text Data Analytics

The most popular form of data analytics in auditing firms is data visualization, which is the graphical representation of information and data (Wilson & Dennis, 2024). However, in terms of data analytics, text data analytics appears to be the most popular form of data analytics in audit firms (Henry, Holtzman, Rosenthal, & Weitz, 2023). Text Data Analytics is the process of extracting high-quality information out of huge volumes and varieties of unstructured texts (mainly from emails, internet and social media). In other words, it is a machine learning technique used to automatically extract valuable insights from unstructured text data.

A substantial volume of textual data is produced and circulated throughout a company's operational procedures, including regulatory filings, conference call transcripts, press releases, earnings announcements, management conversations and analyses, business contracts, news articles, and social media communications. Textual data offers insights into numerous facets of a business from diverse viewpoints. Management discussions and analyses provide the management's viewpoint on the company's present financial condition and future outlook, analysts' reports encompass retrospective evaluations of historical events and projections of future earnings and cash flows, while social media posts may feature advertisements, product reviews, and news announcements.

Textual analysis can be automated by deep learning; specifically, text data can be categorized according to relevant attributes. Additionally, a deep learning model can be trained with transcripts of questions and answers from conference calls—categorized as good, negative, or neutral regarding sentiment—to forecast future conversations. The entire process can be executed autonomously, yielding a machine-readable outcome. A deep learning model converts qualitative information, which previously necessitated substantial human effort for interpretation, into quantitative data that can be seamlessly merged with other data for enhanced audit analysis.

Deep learning algorithms enhance audit evidence by detecting relevant concepts or subjects, recognizing entities (e.g., individuals, locations, events, corporations), extracting emotions (e.g., anger, joy, sadness, disgust), and comprehending subject-action-object relationships. Furthermore, they can associate concepts with a document and categorize them appropriately.

Thus, textual analysis is more appropriate for unprepared content (such as the Q&A segment of conference calls, Facebook status updates, and blog posts) than for prepared content (e.g., press releases and the presentation segment of conference calls). In contrast to planned content, unprepared content may contain slang, idioms, and other linguistic indicators that reveal the speaker's cognitive processes (Druz, Wagner, & Zeckhauser, 2015), potentially signaling audit risk sensitive subjects of interest to the auditor.

Audit Report Lag

Audit report lag (ARL) refers to the duration between a company's fiscal year-end and the issuance date of the audit report, and is sometimes regarded as the primary predictor of financial reporting timeliness. Lee and Jahng (2008) assert that the Audit Report Lag (ARL) is the duration between the conclusion of a company's financial year to the issuance of the audit report. The word refers to the postponed release of the auditor's opinion regarding the accuracy and fairness of financial information prepared by management, also known as audit delay. This requirement ensures the relevance and reliability of financial accounts in timely financial reporting for critical decision-making. However, longer audit report lag may indicate that the auditor is taking the time necessary to thoroughly review and verify the financial statements, which can indicate higher quality work. This is especially so given that auditors are required to exercise reasonable degree of professional skepticism in approaching the audit engagement, an exercise that is often time-consuming, thus, elongating the ARL. Another index which underscores the use of ARL as audit quality is client's operational complexity. Audit report lag can also reflect the complexity of the audit, with more complex audits requiring more time to complete. Wermert, Dodd, and Doucet (2000) and Bamber, Bamber, and Schoderbek (1993) identify two critical events that directly influence Audit Delay. The first factor is the duration required by the client organization to finalize its accounts and prepare draft unaudited financial statements for external audit, while the second factor is the time taken by external auditors to conduct the audit and complete their examination of the draft unaudited financial statements prior to issuing their opinion in the form of an auditor's report to the shareholders of the client organization.

Of the various indices that underscore the utilization of ARL as an indicator of audit quality, two are particularly pertinent to the present study. The first is 'timeliness,' whereas the second is thoroughness, which is more conceptually rooted in audit literature as 'professional skepticism.' Boyne and Law (1991) assert that the annual report serves as a means of fulfilling accountability, while Marton and Shrives (1991) observe that it is the most extensive document accessible to the public, making it the primary vehicle for disclosure. Bamber, Schoderbek, and Bamber (1993) assert that audit delays are positively correlated with the length of audit work, negatively correlated with incentives for timely reporting, and positively correlated with the degree to which an auditor utilizes a structured audit methodology. The delay in audits is inversely related to the concentration of customer ownership or corporate control (Bamber et al. 1993). This has become a concerning issue for investors and stakeholders who require the audit report for decision-making purposes. The postponement of the audit report may erode investor confidence in the reported findings and exacerbate the agency problem.

Professional skepticism is an essential element of auditing, characterized by the maintenance of a questioning mindset and the critical evaluation of offered evidence and reasoning. The auditor's primary role is to mitigate potential operational risks during the audit and to uphold reasonable skepticism throughout the audit process. The presence of presumptive uncertainty regarding evidence is likely to cause delays in audit reports as time progresses.

Therefore, two conflicting attributes contend for supremacy in using ARL as indicator of audit quality; the 'efficiency' attribute or hypothesis, and the 'professional skepticism' attribute or hypothesis. Under the 'efficiency' perspective, shorter audit report lag indicates greater audit quality as it ensures timely availability of the stewardship accounts to stakeholders, thus, reducing the agency conflict, which is occasioned by information asymmetry. On the other hand, the 'professional skepticism' hypothesis on ARL as audit quality indicator presupposes longer ARL. For instance, ARL literature has confirmed that lengthier ARL increases the likelihood of future restatements, (Blankley, Hurtt & MacGregor, 2014, 2015). It is arguable that such restatements are manifestations of extensive substantive tests which result from the auditors' professional skepticism. Professional skepticism is positively associated with audit quality, (Chen, Wang & Liu, 2023), even though it tends to elongate ARL due to its bias towards extensive substantive tests.

Development of Hypothesis: TDA and ARL

The Policeman Theory of auditing emphasizes the importance of auditors' role in ensuring the accuracy and reliability of financial statements. Text data analytics can enhance auditors' ability to detect material misstatements, thereby supporting their role as watchdogs. By leveraging text analytics, auditors can enhance risk assessment, and increase accuracy, but at cost of lengthier reporting lag. As alluded to by Rezaee *et al*. (2017), utilization of text data influences audit latency. This aligns with the policeman theoretical leaning, since accounting information systems enhanced by text data analytics can enhance the auditor's professional skepticism and serve as a catalyst for deeper and wider audit scope, (Barr-Pulliam *et. al*., 2023; Austin *et. al*., 2021; and Gefen *et. al*., 2020). Also, study by Rezaee *et al*. (2017) indicates that text data analytics can affect audit reporting lag, as the extraction of text data requires the amalgamation of various data sources (e.g., emails, web pages, Facebook, WhatsApp, etc.) into conventional accounting information systems, thereby broadening the range of audit evidence acquisition beyond traditional source documents. Thus, contrary to the expected benefits of improved efficiency, a number of studies serve as evidence that the use of data analytics in auditing can lead to elongated audit report lag.

Empirical evidences that support the positive correlation between ARL and TDA abound. Alles and Gray (2016) evaluated the challenges of auditing in the era of big data and notes that the use of data analytics can lead to increased audit complexity and elongated audit report lag. Similarly, Berton (2017) examined the impact of big data on audit timing and finds that the use of data analytics can lead to increased audit report lag. Also, Janvrin and Bierstaker (2016) studied the potential impact of big data on audit quality and notes that the use of data analytics can lead to increased audit complexity and elongated audit report lag. Krahel and Titera (2015) examined the consequences of big data on auditing and finds that the use of data analytics can lead to increased audit report lag. Wang and Tuttle (2017) examined the impact of big data on audit report lag and finds that the use of data analytics can lead to increased audit report lag.

From alternative perspective, it is also arguable, with empirical facts, that text data analytics can reduce audit report lag. The Policeman Theory of auditing posits that auditors act as watchdogs, ensuring that management's financial statements are accurate and reliable (Mautz & Sharaf, 1961). Text data analytics can enhance auditors' ability to detect material misstatements, thereby reducing audit reporting lag. This line of thought takes its root analogically from the Efficient Market Hypothesis (EMH). While primarily used in finance, EMH can also be applied to production processes, (Brynjolfsson & Hitt, 2000). The EMH perspective suggests that technology can increase efficiency by providing real-time information, reducing transaction costs, and enabling faster decision-making. In the current case, the shorter time is derivable since TDA can be implemented on continuous basis, hence eliminating the necessity for management representations, since the transactions that amount to the respective cumulative balances are reliable.

Empirically, negative ARL responsivity of TDA is supported by Brown-Liburd and Vasarhelyi (2015) who showed that big data, including text data analytics, can improve audit efficiency and reduce audit report lag. In reviewing existing literature on text data analytics, Chen and Wang (2017) also suggests that text data analytics can improve audit efficiency and reduce audit report lag. On their part, Dai and Vasarhelyi (2016) developed a theoretical framework for auditing with big data, including text data analytics, and suggests that it can improve audit efficiency and reduce audit report lag. In the same vein, Krahel and Titera (2015) examined the consequences of big data, including text data analytics, on auditing and suggests that it can improve audit efficiency and reduce audit report lag.

Therefore, in light of these divergence in empirical literature, there is uncertainty, especially in Nigerian context regarding *a priori* expectation on ARL responsivity of TDA, as both positive and negative effects are possible. We therefore suggest the following hypothesis in null form for testing:

H_{01}: Text data analytics does not significantly impact audit report lags of listed manufacturing firms in Nigeria

METHODOLOGY

A survey method was used in conjunction with *ex post facto* design. The study was based on examination of the causal relationship between Text Data Analytics and Audit Report Lag of listed manufacturing firms in Nigeria.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VI June 2026

The population of interest to the current study is listed manufacturing firms in Nigeria. According to Nigerian Exchange Group (2024), there are a total of fifty-eight (58) listed manufacturing companies in Nigeria, falling under consumer goods and industrial goods manufacturing subsectors. Manufacturing sector was selected because it has the highest pool of reporting entities among the sectors of the Nigerian Exchange Group, and also because manufacturing business process is heavily information-intensive due to inherent dynamism of the operating environments. Hence, all the manufacturing firms listed on the Nigerian Exchange Group (2024) constitute the population of the study.

A judgmental technique, which is a form of non-probabilistic sampling method, was used because of the need for every sample member to meet certain inclusion criterion. The inclusion criterion was contingent on being quoted on the floor of the Nigerian Exchange Group as at 31st December 2023, having full 12-months accounting year that ended on or before the same date, and having annual report audited.

The sampling procedure began with a census of all the quoted manufacturing firms that published their annual reports for 2023 which disclosed the audit/accounting firm that produced the audit report on the financial statement. For the 2023 fiscal year, a total of thirty-seven (37) listed manufacturing companies were audited by eighteen (18) audit firms. Of these numbers, thirty-three (33) listed manufacturing companies which were audited by fourteen (14) audit firms eventually made up the sample of the study.

With respect to data collection method, data on audit opinion accuracy were sourced from the 2023 annual financial statement of listed manufacturing firms. Collections were mostly done via electronic means through the internet from the websites of the sampled firms. On the other hand, Likert-type questionnaire instrument was used to collect primary data on Voice Data Analytics through the assistance of online-based research assistant (Monkey survey). Table-1 presents a summary of operational measurement of variables.

Table 1: Summary of Operational Measurement of Variables

Variable	**Operational Constructs Used**	**Operationalization**
Text Data Analytics	• Reliance on internet sourced audit evidence in text form	Principal Component Analysis
	• Reliance on client's live streaming transaction data for audit evidence in text form	
	• Resolution to develop capability in textual evidence extraction from online	
	• Accordance of priority to sourcing for textual evidence in audit program	
Audit Report Lag (ARL)	Total time delayed between financial year-end and audit report certification Date Where: N = number of days between audit report certification date and balance sheet date; TA = book value of total assets, standing in for size; TL = total liabilities, representing leverage, and AF = audit fee, standing in for operational complexity	$= \mathrm{Ln}\left[\mathrm{N}\left(1 - \frac{\mathrm{AF}}{\mathrm{TA} - \mathrm{TL}}\right)\right]$

In empirical form, ARL is modeled as follows:

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VI June 2026

$$ARL_i = b_0 + b_1 TDA_i + e \qquad (1)$$

where b_0 is the intercept of the regression equation, b_1 is ARL response coefficient of TDA; and e is error term. In line with the policeman theory of audit, our *a priori* expectation for b_1 is such that:

$b_i > 0$ (in which case the 'professional skepticism' argument is upheld), or $b_i > 0$ (in which case the 'efficiency' argument is confirmed).

RESULT

Field Report

Table 2: Questionnaires Response Statistics

Respondent's Category	Quest. Issued	Returned	Response Rate (%)	No Returned	Discarded	Retained for analyses
Big-Four	21	21	100	0	0	21
Non-Big Four	16	12	75	4	0	12
Total	**37**	**33**	**89.2**	**4**	**0**	**33**

Source: Field Survey (2024)

Of the 37 copies issued, 33 representing 89.2% were returned and four (4) were not returned. The 33 returned questionnaire copies retained for analyses came from 14 audit firms, as responses were based on clients-specific experiences. The configuration of 'clients-to-auditors' ratio frequency of the 33 respondents was such that the mean score was 2.4 and the standard deviation was 2.2. Thus, based on 95% confidence interval, there was a 'clients-to-auditor' ratio of between 1 to 4 on the average, indicating how the audit market is concentrated.

Demographic Data Analysis

With regards to the respondents' category, there is strong evidence of market concentration in the Nigerian audit industry. This is a confirmation of market dominance by the big-four audit firms as captured in the pie chart presented as figure-1.

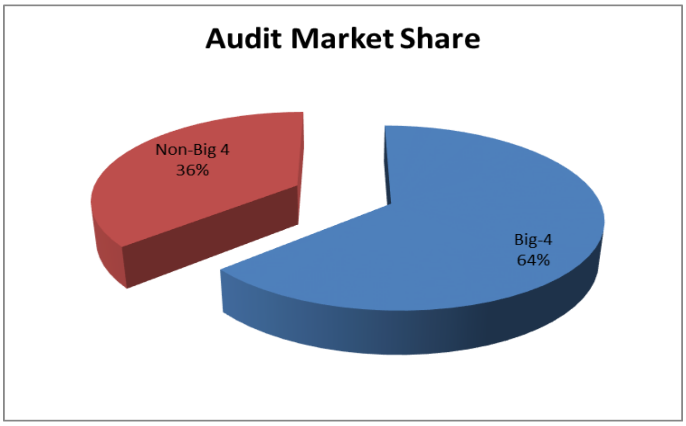

Figure 1: Structure of the Nigerian Audit Industry

The respondents whose opinions we eventually use used mostly fall within youthful age brackets. The implication of this demography is that, a reasonable degree of reliance can be placed on their judgment concerning ICT and data analytics. None of the respondents is older than 45 years as reported in Table-3.

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Table 3: Respondents' Demography: Ages

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	20 – 25	5	15.2	15.2	15.2
	26 – 35	12	36.4	36.4	51.5
	36 – 45	16	48.5	48.5	100.0
	Total	33	100.0	100.0	

Source: IBM SPSS Statistics 20

More so, a good proportion of the respondents are on senior manager cadre, meaning their opinions on the subject of inquiry are reliable. This position is valid based on the premise that staffs at higher strategic apex have greater access to company information than those at lower level. Table-4 presents distribution of respondents' designations, indicating their ranks/statuses and accessibility to prime information about the practices of their employers.

Table 4: Respondents' Demography - Designations

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Audit Manager	21	63.6	63.6	63.6
	Audit Supervisor	7	21.2	21.2	84.8
	Junior Auditor	5	15.2	15.2	100.0
	Total	33	100.0	100.0	

Source: IBM SPSS Statistics 20

As a further tribute to the credibility of their collective opinion on the subject at hand, each of the respondents has adequate educational qualification related to the subject of study. In fact, the adequacy of their educational qualification is skewed in the direction of higher degree of learning as lucidly demonstrated in Table-5:

Table 5: Respondents' Demography - Educational Qualification

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	BSc/BA	12	36.4	36.4	36.4
	MSc/MBA	13	39.4	39.4	75.8
	PhD	8	24.2	24.2	100.0
	Total	33	100.0	100.0	

Source: IBM SPSS Statistics 20

The general notion that, gender plays a role in shaping the preferences and usage patterns of individuals when it comes to technology, implicates an imperativeness for balanced gender representation in text data analysis

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discuss. As reported in Table-6, there is fair gender representation among the respondents, hence lowering the risk of one-sided perspective on the subject-matter.

Table 6: Respondents' Demography - Sex/Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	8	24.2	24.2	24.2
	M	25	75.8	75.8	100.0
	Total	33	100.0	100.0	

Source: IBM SPSS Statistics 20

Overall, all factors that contribute to a good credibility score for testimonies and opinions from survey participants—namely, maturity, experience, knowledge quotients, and accessibility of information on the subject of the opinion—show high scores, attesting to the validity and reliability of sampled opinions. Furthermore, in-depth interviews the researcher conducted with seasoned audit firm proprietors added value in enhancing the authors' knowledge base.

Univariate Analysis

In this section, descriptive analysis of each respective variable is presented with a view to emphasizing the reliability and validity of estimates obtained.

Text Data Analytics:

Text Data Analytics was measured on the basis of four (4) manifest constructs, each of which was used to frame a close-ended question to elicit responses. Respondents were asked to indicate their opinion against each of the statements using five-point Likert-scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Results from the survey are presented in Table-7.

Table 7: Intensity of Text Data Analytics Manifestation

S/N	Manifest Constructs	SA (5)	A (4)	U (3)	D (2)	SD (1)	Mean	Std Dev	Verdict
1	Reliance on internet sourced audit evidence in text form	2	16	11	2	2	3.4	0.9	Undecided
2	Reliance on client's live streaming transaction data for audit evidence in text form	3	16	9	3	2	3.5	1.0	Undecided
3	Resolution to develop capability in textual evidence extraction from online	3	17	5	7	1	3.4	1.0	Undecided
4	Accordance of priority to sourcing for textual evidence in audit program	3	14	10	4	2	3.4	1.0	Undecided
	Overall Tally	**11**	**63**	**35**	**16**	**7**	**3.4**	**1.0**	**Agreed**

Source: Author's Computation via IBM SPSS Statistics 20

According to Table 7, respondents' collective opinion on the average is 3.4 on the 5-point Likert scale. This indicates an inconclusive prevalence affirmation of Text Data Analytics (TDA) deployment by audit firms in Nigeria. As suggested by the result from Table-7, the high prevalence of TDA is mostly attributed to firms' reliance on client's live streaming transaction data for audit evidence. Item-2 is the highest while the other three items have equally likely prevalence factors.

Cronbach's Alpha was calculated to evaluate the test instrument's internal consistency and reliability. The Cronbach alpha of 0.900 for all the four items indicates an acceptable level of internal reliability and consistency.

Principal Component Analysis (PCA) was utilized to convert the data from ordinal to interval scale and to ascertain whether the four (4) elements that comprised the Text Data Analytics measure were unidimensional. The rationale that justifies the use of PCA is the imperativeness of scale congruence since the dependent variable is on an interval scale.

Table 8: Total Variance Explained (Text Data Analytics)

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	3.107	77.671	77.671	3.107	77.671	77.671
2	.552	13.806	91.477			
3	.214	5.342	96.819			
4	.127	3.181	100.000			
Source: Author's Computation via IBM SPSS Statistics 20						

According to the result on the factor analysis in Table 8, there is only one component that was extracted which explains 77.7 per cent of the total variance, with an Eigen value of 3.107. This means more than three (3) out of the four (4) items used to measure TDA were able to go in the same direction in the measurement of the variable.

To test for the suitability of carrying out a factor analysis, a KMO-Bartlett test was carried out and the result reported in Table 9.

Table 9: KMO and Bartlett's Test

Tests		**Test Statistics**
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.810
Bartlett's Test of Sphericity	Approx. Chi-Square	91.444
	Df	6
	Sig.	.000

Source: Author's Computation via IBM SPSS Statistics 20

The results strongly confirm the suitability of carrying out PCA since the p-value of Bartlett's test of sphericity is less than 0.05 and the high values of the KMO statistic (0.810) which generally indicate that a factor analysis is useful with the data.

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Audit Report Lag

ARL was operationalized in terms of natural logarithms of the number of days between the dates the audited annual reports were signed by the auditor, and the balance sheet date, after controlling for the effects of leverage, firm size and operational complexities.

Descriptive statistics in figure 4.3 relates to the ARL as obtained from the field.

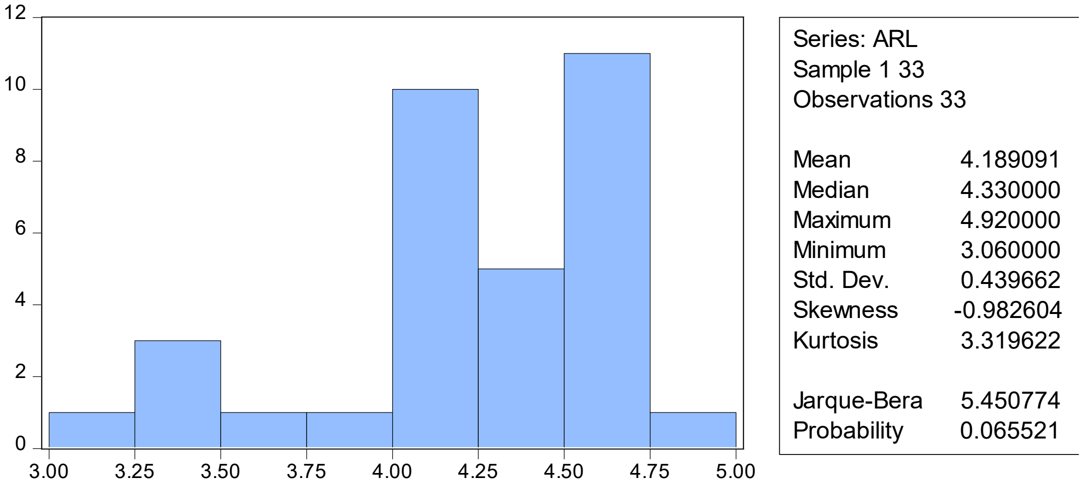


Figure 4.3: Audit Report Lag in Nigeria

The average number of days is approximately 66 days (i.e., $e^{4.1891}$) in terms of mean, or approximately 76 days (i.e., $e^{4.3300}$), or approximately 91 days (i.e., $e^{4.51}$) in terms of modal score, with a standard deviation of 1.6 days (i.e., $e^{0.43966}$). The maximum and minimum ARL are approximately 137 days (i.e., $e^{4.92}$) and 21 days (i.e., $e^{3.06}$) respectively. Given the near-equality of the two measures of central tendency, and despite the slight skewness (-0.9826), ARL is fairly symmetric or normally distributed as the Jarque-Bera statistic (5.451) and its probability value indicate.

Evaluation of Hypotheses on Text Data Analytics and Audit Report Lag

In this subsection, the objective is to test the null hypotheses (H_{01}) for statistical significance in predicting ARL responsivity of TDA, on which basis we are to either confirm or reject the hypotheses. Rejection criterion, is 5% level of significance. If the p-value of the coefficients is less than or equal to 0.05, then the related hypothesis is rejected, otherwise it is confirmed.

To evaluate the stated hypotheses requires the estimation of the model earlier stated in section 3, using the transformed data. The estimated coefficient results are reported in Table 10a.

Table 10a: Coefficient of the Regression Equation of ARL

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.189	.050		84.045	.000
	Text Data	.337	.051	.768	6.667	.000
a. Dependent Variable: ARL						

According to the produced result, coefficients of TDA is 0.337 which has positive sign. The probability value of TDA is way below the 0.05 threshold; hence it is significant.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VI June 2026

Table 10b: Model Summary[b]

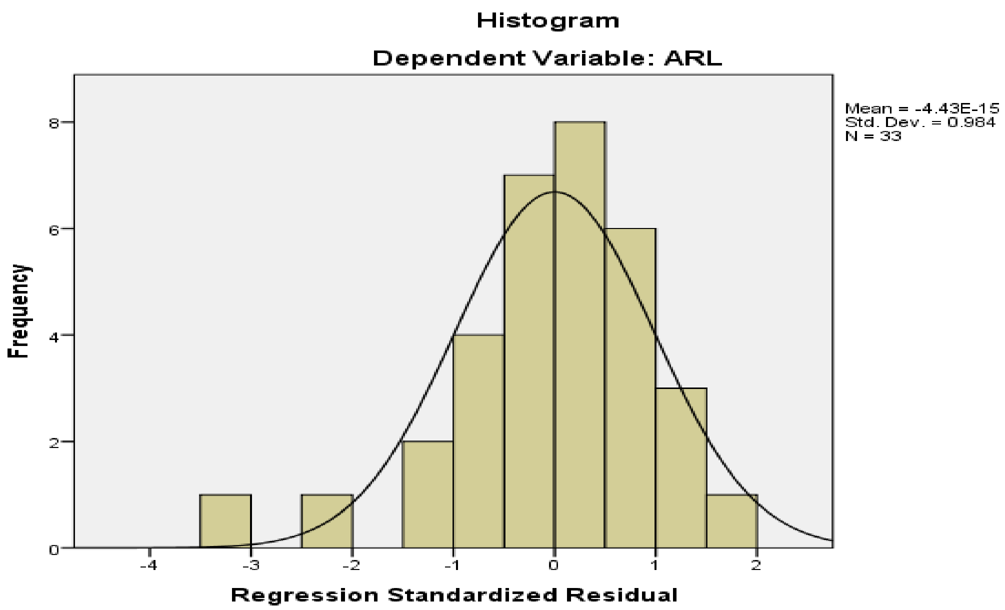
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.768[a]	.589	.576	.28633	2.112
a. Predictors: (Constant), Text Data					
b. Dependent Variable: ARL					

With respect to diagnostics which are reported in table 10b (model summary), the reported Durbin-Watson statistic indicates near absence of autocorrelation, hence there is need to worry over autocorrelation. Also, the R-square (or the coefficient of determination) shows that approximately 58.9% of ARL variability can be attributed to the changing dynamics of TDA among manufacturing firms in Nigeria.

Table 10c: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.644	1	3.644	44.450	.000[b]
	Residual	2.542	31	.082		
	Total	6.186	32			
a. Dependent Variable: ARL						
b. Predictors: (Constant), Text Data						

Also, with respect to the model's goodness-of-fit, Table 10c presents the ANOVA result which underscores the reliability and validity of the model due to its estimation accuracy in fitting the data.



Finally on diagnostics, normality test result, which is in the form of histogram, shows that the error terms are approximately normal in their distribution, confirming that our linear estimation is in line with the requirements of Ordinary Least Squares.

In conclusion on the hypothesis testing therefore, there is no statistically justifiable reason for us to accept the null hypothesis. We therefore strongly reject the hypothesis that text data analytics does not significantly impact audit report lags of listed manufacturing firms in Nigeria. This means, TDA is empirically proven to be a significant stimulant of ARL.

DISCUSSION OF FINDINGS

Regarding how text data analytics influence audit report lag, this study has produced empirical evidence that supports existence of positive impact of text data analytics on audit report lag. Thus, results appear to confirm that auditors' use of text data analytics expands their reach by giving them access to more types and volumes of data than they would have, using conventional auditing methods. Having access to greater data volumes kindles auditors' professional skepticism. This line of thought runs in tandem with several studies that have investigated the effect of data analytics on auditors' professional skepticism, with some suggesting that the use of data analytics can improve professional skepticism. For example, Barr-Pulliam *et. al.,* (2023) and Austin *et. al*., (2021) found that auditors who used data analytics to identify fraud risks were more likely to exercise professional skepticism than those who did not. Another study by Brazel *et al.* (2016) found that the use of data analytics can improve auditors' professional skepticism by reducing the influence of outcome bias. Yet another study by Gefen *et. al*., (2020) found that the use of data analytics can improve auditors' professional skepticism by increasing their confidence in their judgments.

The study's findings also necessitate caveat on associating audit report lag elongation with audit quality. For instance, poor data quality might also lead to inaccurate results, requiring additional time to resolve. This is so, especially given the technical difficulty auditors usually face in coping with clients' poor big-data-harnessing capabilities in Nigerian auditing industry, (Bonsu et al., 2023). Generally, deployability of big data analytics by auditors depends largely on the quality of data harnessing capability of their clients (Li, 2022). Where the clients' do not have the capability to harness big data, auditors will not have the raw materials to feed into their analytics software. Or where the clients have poor quality data, as is rampant among audit clients in Nigerian (Bonsu *et al.,* 2023), then audit report lag may be elongated unproductively. For instance, lack of proper coordination in harnessing the requisite data might lead to data overload. Analyzing large volumes of unstructured text data (emails, social media, etc.) can lead to data overload, causing auditors to spend more time sifting through irrelevant information. Such circumstance easily generates false positives, requiring auditors to spend more time verifying results. It is therefore instructive to note that, while text data analytics can bring many benefits, it is important to be aware of these potential challenges and plan accordingly to avoid elongating the audit report lag.

CONCLUSION AND RECOMMENDATION

Conclusion

This study has produced evidence that the manufacturing industry in Nigeria presents a fertile ground for text data analytics to sprout. This is mostly made possible due to possibility of seamless integration of enterprises' Management Information System with external digital platforms, such as emails, e-commerce platforms, internet banking and social media platform. The fact that most businesses conduct their transactions electronically, it means gathering text data for analysis do not pose much challenge to most businesses. Data can be retrieved and put into productive use with ease, hence the high prevalence of text data analytics among manufacturing firms in Nigeria, (Bonsu *et. al*., 2023). It is therefore conclusive, that text data analytics has the potential to contribute to audit quality.

The study's conclusions have important applications for a range of stakeholders. The findings highlight the need for ongoing professional development for practitioners in order to preserve traditional competencies like ethical reasoning and critical judgment while fostering technology and strategic skills. These observations highlight how crucial lifelong learning is to adjusting to the changing needs of technology. This study emphasizes to regulators and legislators how urgent it is to update accounting and auditing standards to take into account the realities of text data analytics. To preserve the public's confidence in the accounting profession, updated frameworks must handle ethical issues such data protection, openness, and fairness. Other important parties involved in this change are training facilities, educators, and academic institutions. The need for curricular changes that equip aspiring auditors to handle multidisciplinary difficulties is highlighted by this study. In order to guarantee that future professionals are prepared to meet the complex needs of Industry 6.0, these changes should incorporate training in technology, governance, and sustainability.

Recommendations

In light of the result showing positive influence of text data analytics on audit report lag, we make the following recommendations:

- For Auditing Firms
  - Enhance auditor training: Provide ongoing training for auditors on text data analytics and its applications in auditing.
- For Regulatory Bodies
  - Encourage adoption of text data analytics: Promote the use of text data analytics in auditing through guidelines, standards, or incentives.
  - Develop standards for text data analytics: Establish standards for the use of text data analytics in auditing to ensure consistency and reliability.
- For Audit Committees and Boards
  - Provide resources for audit innovation: Allocate resources to support the adoption of innovative audit technologies, including text data analytics.

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