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Effect of Big Data Analytics on Audit Evidence

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Abstract

The purpose of this study is to determine the effect of the application of big data analytics (BDA) on audit evidence. A descriptive/cross sectional survey design was adopted while random sampling was used to distribute 514 structured questionnaires drawn on four Likert scale to auditors in private practice in South-West, Nigeria. 362 copies of the questionnaire were validly returned and successfully tested for reliability and validity. These were analysed using regression analysis and the results revealed that all elements of audit evidence considered – control tests, sufficiency, assertions on financial statements and relevance/reliability – were positively and significantly affected by the application of BDA. The study recommends that audit firms of all tiers should embrace the application of BDA in sourcing for audit evidence and that, as a matter of urgency, standard setting boards should consider issuing a standard to drive the process.

Key words: *big data; big data analytics; audit evidence;*

JEL Classification: *M42*

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1. Introduction

With the introduction of electronics in accounting systems, traditional audit is no longer adequate. The procedures remain the same, but the difference lies in the adoption of appropriate audit software for the execution of auditing assignments. In this context, Kamil and Nashat (2017) consider as new challenges to audit activities issues such as: the loss of audit trail, the need for protection of information and the exposure of data to viruses. Modern audit brings new methods for collection and evaluation of data for compliance and substantive tests. There will definitely be a paradigm shift in accounting and auditing with the emergence of artificial intelligent (AI) as "auditing is particularly suited for applications of data analytics and artificial intelligence because it has become challenging to incorporate the vast volumes of structured and unstructured data to gain insight regarding financial and nonfinancial performance of companies" (Kokina and Davenport, 2017, p. 116). "The quantity of data produced by and available to companies, the replacement of paper trails with IT records, cloud storage, integrated reporting and growing stakeholder expectations for immediate information – any one of these alone would affect the auditing process, but Big Data is bringing them all, and more, at the same time" (ACCA, 2015 quoted by Salijeni et al. 2018).

Similarly, when a comprehensive view on big data is considered, big data should be described as high-volume, high-velocity and high variety information assets that demand cost-effective and innovative forms of information processing (Rai, 2020; Omitogun and A-Adeem, 2019). This enhances insight, decision – making and process of automation. Data available in today's business space is not limited to structured data but also include vast unstructured data such as data sourced from email, Twitter, Google and other social media platforms, as these are continuously increasing in volume and there is a need for a sophisticated tool called *Big Data Analytics* (BDA) to retrieve and generate useful information.

BDA has become a major game changer in both financial reporting and auditing. Yoduwati and Alamsyah (2018) assert that with the help of BDA, structured and unstructured data can be processed faster, and BDA tools also support data mining, social network analysis and test analysis which eventually enhances business value. This highly welcome development through information technology has brought new opportunities and challenges for the accounting system. The ever-increasing volume of generated data brought in the concept of *big data* (BD) the application of which, in accounting and auditing, rides on the existence of automated accounting systems. This is to say that big data analytics can only be implemented through automated accounting systems, which, in turn, promotes real time audit. This age of information technology is characterised by an abundance of data and, at the same time, accountants and decision makers face the difficulty of processing this vast data to derive its full benefits (Younis, 2020).

The advent of big datasets raises the need for a robust analytical tool with which to draw useful inferences from arrays of data and this brings the need for big data analytics (BDA). The need for BDA is pronounced in auditing as much as it is in other facets of live, and it is no wonder that the big tier audit firms have already designed appropriate tools for its use. It is reported that PwC uses Halo for general ledger analysis and audit, while KPMG uses IBM's Watson for general ledger analysis and audit of clients' data. Deilotte employs Argus for AI and Optix for data analytics (Kokina& Davenport, 2017), while Ernst & Young developed Helix which is programmed to analyse the general ledger and to help audit teams present and organize financial data, such as inventories, payables, revenue, trade payables etc. (E/Y Web, 2022). Medium and small tier audit firms use off-the-shelf software such as Lavastorm, Alteryx, Microsoft's SQL (ICAEW, 2016).

Audit practices in Nigeria are not in any way different from what can be observed in other parts of the world as the economy is confronted with the benefits and challenges of big data and the public accounting firms in Nigeria adopt the same software for the management of big data requirements. This study is therefore carried out to provide an empirical investigation into the effect of big data analytics on audit evidence in Nigeria using the South-West Zone as a research setting.

The following hypotheses were formulated and tested at 95% confidence level:

H1: Big data analytics has a significant effect on compliance tests.

H2: Big data analytics has a significant effect on the sufficiency of audit evidence.

H3: Big data analytics has a significant effect on the relevance and reliability of audit evidence.

H4: Big data analytics has a significant effect on the assertions on financial statements.

2. Review of related literature

2.1. Big Data and Big Data Analytics

The ever-increasing volume of data has given birth to the concept of Big Data (BD). Big data refers to structured and unstructured data sets that are commonly described in terms of four Vs: Volume, Veracity, Velocity and Variety (Gepp *et al*, 2018). BD has gone steps further in term of description as extant literature no longer describes it in terms of four, but rather seven Vs: Volume, Velocity, Variety, Veracity, Visualisation, Value and Variability (Riati *et al*., 2016).

Volume: This is the size of data being processed in nanoseconds. For the data to be regarded as big, the database should exceed Petabyte. A petabyte is one million quadrillion bytes which is equivalent to 20 million filing cabinets worth of text (Nwadialor and Nwadi, 2020). In terms of size, the next phase is Exabyte which is already in the waiting. The generation of data is expected to be continuous and to expand faster. This is one of the reasons why the traditional sampling technique may no longer be adequate; hence the need for the deployment of big data analytics tools that will guarantee seamless interaction with the available vast data. This is the essence of control and substantive testing through which a public accountant confronted with the big data phenomenon obtains evidence to justify expression of opinion.

In fact, Omitogun and Al-Adeen (2019) reason that: "with business operations expanding globally, the role of the audit profession has become more prominent, and the greater amount of captured data has resulted in massive transaction volumes. The real time capture of transaction data, including location, time, amount and medium, can ease the process of gathering substantive evidence for development of an audit opinion."

Velocity: This is the speed or rate at which data are generated from different sources in an instantaneous and continuous manner. Nwadialor and Nwadi (2020) report that "Walmart collects more than 2.5 petabytes of data every hour from its customers' transactions". To audit such operations is beyond the capabilities of traditional sample testing which makes it imperative to deploy BDA, which permits continuous and complete testing of data.

Variety: In a big data environment, data available to management is not only structured and financial but also includes unstructured and non-financial data, which is generated from various sources such as Journal, Twitter, Google etc.

Veracity: This, according to Young (2020) is all about the reliability of data, as the interest of the beneficiary is about the quality of data. Application of BDA stands to enhance data quality in a BD database.

Value. According to Wamba et al. (2015) value is "the extent to which big data generates economically worthy insights and/or benefits through extraction and transformation".

The available data must be amenable to analysis otherwise it is a useless and worthless data.

Visualisation. According to Chu and Young (2021), "auditors have begun to use visualisation as a tool to look at multiple accounts over multiple years to detect misstatements". To derive useful information from image, video and audio data and to interrogate unstructured data, BDA becomes a very necessary tool.

Variability: Big data are characterised by intrinsic variability. Variability can also refer to the inconsistent speed at which big data is loaded into a database. There is therefore the need to find anomalies and to deploy outlier detection methods in order for any meaningful analysis to occur. Sun, Strong and Li (2018) bring another dimension into the description of big data as the study suggests ten classifications of big data and these are: big volume, big velocity, big variety, big veracity, big intelligence, big analytics, big infrastructure, big service, big value and big market.

However, with all these descriptions and classifications of big data, what is paramount for auditors is to successfully interrogate big data in such a way as to enhance the outcome of audit services. BDA becomes the effective tool through which auditors, whether internal or external, can interact with clients, of which operations are largely driven on big data platforms.

Notable changes to accounting practices are mostly as a response to changes in the business environment and to business accounting needs. According to Omitogun and Al-Adeem (2019), book-keeping, a written manifestation of merchants' affairs was developed to meet business needs. Financial accounting reporting represents the supply of information to both internal and external users, especially to the management of an organisation to appraise its performance and for the investors to determine the overall value of their investment in an organisation. The process of this information disclosure warrants that accountants collect, process and analyse vast financial and non-financial data. Furthermore

Omitogun and Al-Adeem cited Alles (2015) which states that accounting and data ”have a strong interdependency, which is a consequence of ongoing business transactions”, and with the increasing volume of transactions and of the data available, a review of audit approaches and procedures is necessary.

The quantum of data being generated to support business operations, decisions and measures of performance is becoming enormous. The requirements of audit to meet the necessities of a changing operating environment together with the significant growth in the volume of transactions and the increase (in complexity and volume) of available audit evidence, motivated auditors to seek more cost-effective approaches to audit planning.

If advanced economies are coping with the challenges of big data in accounting and auditing, the same cannot be claimed of emerging economies such as Nigeria. While there is evidence that the big four are relying on the use of modern tools in the conduct of their business, yet the same cannot be asserted of numerous small tier audit firms in Nigeria. The latter are forcefully confronted with big data challenges as their clients are small sized businesses, but there are off-the-shelf BDA software that could be used and there is also a pool of technically capable professionals that such firms can engage in the execution of their audit engagements, if their clients' operations are best fitted into big data description.

The importance of big data in auditing lies on the platforms that serves as analytical tools, hence the term big data analytics (BDA). Big data is the process of analysing data with the objective of drawing meaningful conclusions (Ernst & Young, 2015). Technological advances and new procedures, such as the exploration of large sets of relevant data from internal and external sources, may produce audit evidence, which, according to Siroisa and Savovska (2017), can be used in risk assessment, analytical procedures or substantive and control testing These provide for the importance of BDA, especially in the process of obtaining audit evidence through compliance and substantive tests.

2.2. Big Data analytics and audit evidence

Audit evidence in a big data environment has positive and negative sides. There is an increase in reliability, as the most reliable sources of evidence are those which allow for the data to be obtained from outside the organization and, with the advent of big data, sources of data are now formal and informal, as external data can be sourced from Facebook, Twitter, Path, Instagram, Email etc. Both structured and unstructured data are now stored and retrieved from the cloud.

The flows of such data are not so easy to trace or follow as within a traditional accounting system, hence the major usefulness of BDA which is expected to provide reliable evidence needed to support the expression of audit opinion. According to Mathew (2006), cited by Saljeni (2019), BDA has the potential to improve technical efficiency in audits by enhancing the quality of both the evidence that auditors collect and their professional judgments based on that evidence. This is made possible as, in the era of big data, the volume and veracity of data available to auditors can be reasonably accessed and processed in an efficient manner with the application of BDA tools.

In the traditional paradigm, auditing relies mostly on direct verification of transactions, i.e.: receipts, counting of inventory at regular intervals which could be monthly, quarterly, semi-annually or annually, but this has changed as this approach is no longer efficient or relevant any more under present conditions, especially for clients that are big companies or for some medium sized firms. Technology-enabled audit come with higher quality of evidence, and Moffitt and Vasarhelyi (2013) asserts that this is “derived from many new sources including big data, exogenous data, and the ability to analytically link different processes, database-to-database confirmation, and continuous monitoring alerts”.

However, BDA has changed the paradigm of audit evidence that auditors gather both in term of nature and competence in a big data environment. Dagiliene and Kloviene (2019) suggest that external auditors now possess a very powerful tool most especially for audit of big business enterprises, as BDA stands to enhance the effectiveness and reliability of audit results. In fact ”auditors have more resources available in order to gather evidence needed for their audits and opinion statements” (Balios, et al. 2020). BDA is relevant for audit evidence both in terms of sufficiency, as sufficiency is all about 'Volume and Variety of data', and appropriateness, as the latter provides means for testing of reliability and relevance. Hence, BDA is appropriate for the evaluation of different types of businesses as well as different forms of evidence (IAASB, 2016).

Audit evidence sourced through both control and substantive tests were limited to sampling under the traditional accounting system, especially for large size clients. This procedure of statistical sampling was portrayed as addressing the alleged inability of traditional techniques of gathering evidence in a timely manner to satisfy the demands of a changing corporate environment, which was marked by a considerable increase in the amount of transactions, in the early 1960s (PCAOB (2004). Moreso, it is reasoned that auditors cannot assume that data from third party sources is complete and accurate because IAASB (2016) provides that external data obtained from third party providers may only be an "aggregation of data obtained from multiple sources and may not have been subject to procedures to validate completeness, accuracy and reliability of data", yet these are cornerstones of appropriate evidence.

According to International Standards of Audit (ISAs) (PCAOB 2004) evidence obtained from independent, external source is stronger and more appropriate than evidence obtained from other sources. However, that position appears no longer tenable in the context of BDA. The major challenge for BDA in the establishment of evidence is the fact that the ISAs do not indicate what type of evidence analytics should provide (Ernst & Young 2015). The lack of such provisions is restricting the use of BDA by auditors, especially in the case of statutory (external) auditors.

Similarly, the auditors' concern is related to the manner in which they can obtain appropriate and reliable audit evidence with the effective application of BDA in this era of high volume, velocity and veracity of data available from sources that were hardly imagined a couple of years back. For example, the fair value of intangible assets can no longer be reasonably established using traditional processes. BDA is the most appropriate tool to collect and analyse vast amounts of data on intangible assets. Alteration of transactions' details in the ledger can easily attract auditors' attention in traditional audit procedures, but it is not so easy to identify/locate any alteration in a big data environment, except with the use of BDA tools. In addition, auditors could decide to replicate the accounting system of a client to ascertain the reliability of the system but this poses a challenge in a big data environment. The combined effect of the above is the undermining of reliability and appropriateness of evidence obtained in a BD environment.

Ernst & Young (2015) asserts that BDA "will now transform audit beyond sample-based testing to include analysis of entire populations of audit-relevant data (transaction activity and master data from key business processes), using intelligent analytics to deliver a higher quality of audit evidence." The importance of BDA tools in audit evidence becomes undeniable for public auditors to source and obtain necessary assurance to support overall expression of opinion. ISA No. 500 – *Audit Evidence* grants priority on obtaining appropriate, reliable, relevant and sufficient evidence. Regardless of the size of a business organization or its complexity, independent auditors are professionally bound to the letter of the standards and the execution of audit engagements must be conducted in compliance with such standards. BDA has the capacity to assist auditors to comply with these requirements when auditing a client which operates in a big data setting.

2.3. Theoretical review

The importance of auditing and audit evidence has over the years been supported with the agency theory. The industrialisation of the early eighteenth century brought the challenge of what could be termed as a conflict of interest. The size and scope of big enterprises introduced the need to engage others (i.e., the managers) to manage business interest, whose own interest may conflict with that of the owners. These appointed managers are regarded as agents of the owners (i.e., the principal). This is the root of agency theory popularised by Ross (1973), Mitnicks (1975) and Jenkens & Meckling (1976). In fact, Hair et al. (2021) summarised four theories related to auditing, as follows: agency, inspired confidence, policeman and lending credibility. The agents, due to their daily interactions with the activities of the businesses tend to know more than the owners and they are duty bound to render account of their stewardship to the principal. The owners intend to ensure that the reports of activities as presented by the managers are a true reflection of the business.

A common misconception about agency theory in connection to auditing main purpose is that it gives financial statements more credibility. This is what is referred to as the Lending Credibility Theory. Management uses audited financial statements to increase stakeholders' trust in its stewardship. If decision-makers like investors, the government, or creditors must base their decisions on the information they get, they must have confidence that it accurately depicts the economic worth of the company. In terms of audit research, this lessens 'information asymmetry'. However, the efficient markets hypothesis asserts that investors' decisions are not primarily based on audited information (Mitnicks, 1975).

The theory of lending credibility is very crucial to this study as there is a need for auditors to obtain appropriate and reliable evidence to corroborate findings on both compliance and substantive examination of clients' activities which will enhance the ability of independent auditors to express an opinion deemed appropriate.

2.4. Empirical review

Alrashidi, Almutairiand and Zraqat (2022) conducted a study in order to investigate how BDA affects external audit procedures in the Middle East. The study employed PLS-SEM (3.3.3) for the analysis of data. The study used a questionnaire on a sample of 361 auditors who work in auditing companies in Kuwait, Saudi Arabia, the United Arab Emirates, Jordan, Bahrain, Egypt, Lebanon, and Iraq. To choose the sample, the researchers used a stratified random sampling procedure. The findings showed that BDA has an impact on audit procedures at all phases of the auditing process, where it contributes to information delivery that helps auditors understand the client's internal and external environments, which in turn influences the choices to accept audit assignments. Furthermore, by providing essential information, BDA enables auditors to simply run analytical procedures, estimate client risks, and understand and evaluate the internal control system. As a result, the study recommended that auditors should develop their abilities in the BDA field, as it adds to the creation of additional value for both auditors and their clients. This study did not however address the effect of BDA on audit evidence.

Omitogun and Al-Adeem (2019) carried out an empirical investigation on the auditors' perceptions and competencies related to big data and data analytics. An electronic questionnaire distributed to accountants showed that auditors have good information technology skills and are well-acquainted with big data and data analytics. However, they lack relevant technical skills and are unfamiliar with related data analysis tools, excluding Excel. The results revealed that 64.71% of accountants have not attended any training on big data and data analytics, while 31.37% plan to enhance their related knowledge. Auditors need to obtain training on substantive audit risk assessments using big data and data analytics. The study'sfocus was not on audit evidence, but rather on the need to develop auditors' technical skills for application of data analytics in audit engagements.

A study on Big Data and changes in audit technology by Salijeni *et al.* (2019) explored the most recent episode in the evolution of audit technology, namely the incorporation of BDA into audit firms 'procedures. Drawing on 22 interviews with individuals with significant experience in developing, implementing or assessing the impact of BDA in auditing, together with the analysis of publicly available documents on BDA published within the audit field, the paper provides a holistic overview of BDA-related changes in audit practice. In particular, the paper focused on three key aspects, namely the impact of BDA on the nature of the relationship between auditors and their clients, the consequences of technology on the execution of audit engagements and the common challenges associated with implementing BDA in auditing activities. The study's empirical findings were then used to establish an agenda of areas suitable for further research on the topic. The study is one of the first empirical accounts providing a perspective on the rise of BDA in auditing. The study was a step further compared to existing studies on BDA, but its main focus was not on the effect of data analytics on audit evidence.

Eilifsen *et al.* (2020) carried out an exploratory study on the use of audit data analytics (ADA) in current audit practice. Firstly, heads of professional practice of five international public accounting firms in Norway were interviewed. The study found out that the firms differ in their strategies on how to implement ADA and the general managers report significant uncertainty about the supervisory inspection authorities' response to the use of ADA. Secondly, a questionnaire was administered to 216 engagement partners and managers about their perceptions of ADA and their actual ADA usage on 109 audit engagements. Overall, the attitude towards ADA's usefulness was positive. The analysis of the audit engagements suggests the use of ADA is relatively limited and the use of more 'advanced' ADAs is rare. More ADA tools are used for clients with integrated ERP/IT systems and for newly acquired audit engagements. The study provides details of ADA use on each auditing phase, while findings were mostly analysed from an institutional theory perspective.

Appelbaum (2016) carried out a study on securing big data provenance for auditors, with the purpose of highlighting a main issue regarding reliable audit evidence derived from Big Data – that of secure data provenance. Traditionally, audit evidence external to the client has been regarded as superior to other forms of evidence. However, external 'messy' big data sources that may be material to aspects of the audit may lack provenance and verifiability. That is, the origins of the data may be unclear and its log files incomplete. According to the standards, such evidence should be considered as less reliable as audit evidence. External auditors, as outsiders of the client, should be able to reproduce the data lifecycle or transaction path, which may not be possible in an electronic environment with incomplete provenance. Furthermore, this mapping or provenance of the data origins and history should be securely maintained so that it cannot be thwarted. This need for secure data provenance has been largely ignored by the business community in its haste to use BDA, but has been acknowledge by extant systems research as being an area that requires attention. The study contributes to the discussion of big data provenance through the lens of public company auditing, where the provenance and reliability of data sources and audit evidence are of paramount importance. Also, it proposes a system of secure provenance collection, the Big Data Provenance Black Box, which is derived from several streams of extant research. The study's major concern was how to ensure that evidence obtained through the application of BDA can beat least as reliable and secured as that which is obtained under a manual auditing. The study fails to empirically determine the effect of BDA on audit evidence.

Brown-Liburd and Vasarhelyi (2015) conducted an archival study on big data and audit evidence and the study highlighted that the traditional view on evidence may no longer be adequate in this information age as data can now be automatically captured. The study identified a series of tools such as GPS (tracking devices) that may be relevant for the establishment of evidence of online transactions. The study does not examine the effect of BDA on the audit evidence.

It is clear from the extant literature reviewed that there is an apparent knowledge and empirical gap on the effect of BDA on audit evidence. The purpose of the study is to investigate the existence of such an effect, as the results could be helpful to external auditors, professional bodies and to other institutions.

3. Research methodology

This study employs a cross sectional survey method which permits a one-time collection of data from participants. From a population of chartered/professional accountants, a minimum sample size of 393 was determined. In total, 514 structured questionnaires were administered to randomly selected auditors in private practice in six states of South West Nigeria. 389 were returned but only 362 (70% response rate) were found valid for the purpose of the study. The research instrument was subject to reliability and validity tests and the results are shown in **Table no. 1**.

Table no. 1. Reliability and Validity result

Variables	Items	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
BD and BDA:					
Application in External Auditing	2	0.928	0.894	0.998	0.997
	3	1.064			
BDA – Audit Evidence:					
Compliance Test	1	0.632	0.913	0.851	0.491
	2	0.644			
	3	0.693			
	4	0.635			
	5	0.830			
	7	0.747			
Sufficiency of Audit Evidence	4	0.997	0.927	0.982	0.965
	5	0.967			
Relevancy and Reliability of Audit Evidence	1	0.653	0.816	0.884	0.725
	3	1.032			
	4	0.827			
Assertions on Financial Statements	4	0.906	0.910	0.709	0.563
	6	0.553			

Source: Authors' computation, using SPSS (2022)

Data presented in Table no. 1 shows that the values for the Average Variance Extract (AVE), Composite Reliability (CR) and Cronbach's Alpha (CA) are below the acceptable benchmarks of 0.5, 0.7 and 0.7, respectively. These confirm the reliability and validity of the instrument.

Table no. 2. Sample structure

		Freq.	P (%)
Category of staff	Audit Staff	362	93.1
	Others	27	6.9
Audit Staff	Junior	44	12.2
	Associate	64	17.7
	Semi-Senior Associate	50	13.8
	Experienced/Senior	102	28.2
	Assistant Manager	33	9.1
	Manager	14	3.9
	Consultant	11	3
	Associate Director	3	0.8
	Partner	22	6.1
	Principal Partner	11	3
	Managing Partner	8	2.2

Source: Authors' field survey (2022)

As shown in Table no. 2, of the total 389 respondents, only 362 (approx. 93%) serve in audit related functions and their opinions are classified as valid for the purpose of this study, while the remaining 27 respondents (approx. 7%) work in non-audit services (NAS) and therefore are regarded as not useful for this study**.** Data on the status of respondents reveals that 41 of them (8.6%) are found to be partners and this lend credence to the opinions obtained from them. Furthermore, 61 respondents (16.9%) are managers or equivalent and 102 (28%) are experienced audit staff. The overall implication is that about 56% of the respondents are well experienced in audit engagement activities. Also, about 80% of the respondents are chartered (professional) accountants and generally only about 17% could be regarded as less experienced as they had less than three years working experience in audit service engagements. The cumulative effect of these socio-demographic analyses is that respondents possess the required professional and field experiences needed for expressing their opinions on the matter investigated.

The questionnaire contains various questions diligently constructed based on recommendations from the relevant literature and in accordance with the expectations of standards. The questions were reviewed by academics with research interests in electronic accounting and auditing along with practicing public accountants.

Table no. 3. Measurement of the research instruments

Independent variable	Predictive parameters	No. of items	Sources
1. BDA:	Application in External Audit	2	Appelbaum et al. (2017, 6)
2. Dependent variables: i. Control testing		7	Appelbaum et al. (2017, 6) PACOB 2018-005 (AS 1105.03-08
ii. Sufficiency of audit evidence	Substantive Test	5	Eilifsen et al. (2020,42) Brown-Liburd & Vaharhelyi (2015, 7) Balois et al. (2020, 214) PACOB 2018/2020-005 (AS 1105.03-08, 11& 12)

Independent variable	Predictive parameters	No. of items	Sources
iii. Relevance and reliability of audit evidence	Substantive Test	4	Appelbaum et al. (2017, 6) Halois et al. (2020, 214) PACOB 2018/2020 -05 AS1105, 03-08)
iv. Assertion on financial statements	Substantive Test	6	Appelbaum et al. (2017, 6) Murphy (2014, 1) PACOB 2018/2020 – 005 (AS 1105, 11 & 12)

Source: Authors' projection (2022)

Table no. 3 reflects the summary of various previous studies and of standards that serve as a basis for the formulation of this study's questions. The questions were addressed order to capture the perceptions of the practitioners on the use of BDA in the sourcing of evidence through the conduct of control and substantive tests.

3.1. Quantitative analysis

Regression analysis was adopted for testing the hypotheses of this paper, the results being presented in **Tables no. 4 to 7**.

3.2. Regression results

H1: Big data analytics has a significant effect on compliance tests.

Table 4 (a): Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.884[a]	.781	.781	.54348

a. Predictors: (Constant), BDA: Application in Audit Evidence

b. Dependent Variable: Audit Evidence in BDA: Compliance test

Table 4(b): ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	379.758	1	379.758	1285.699	.000[b]
	Residual	106.333	360	.295		
	Total	486.091	361			

a. Dependent Variable: Audit Evidence in BDA: Compliance Test

b. Predictors: (Constant), BDA: Application in Audit Evidence

Table 4(c): Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.712	.102		6.945	.000
	BDA: Application in audit evidence	.815	.023	.884	35.857	.000

a. Dependent Variable: Audit Evidence in BDA: Compliance Test

Source: Authors' projection (2022)

According to Table 4(a), the coefficient of determination (R^2) is 0.781 which implies that about 78.1% of the variation in compliance testing is explained by the application of big data analytics in audit evidence, while the remaining 21.9% may be due to other factors not considered in this study's model.

The F-value (1,360) = 1285.699 has a related P-value of 0.000 < 0.05. Therefore, the first hypothesis is confirmed, i.e., there is statistical support to state that BDA has a significant effect on compliance testing (Table no. 4(b)).

Table no. 4(c) presents the coefficient of the independent variable (Audit Evidence in BDA: Compliance Test): β1 = 0.884; t-value = 35.857 and p-value = 0.000. This suggests a positive and significant impact of BDA on compliance testing. In addition, it shows that a unit increase in BDAs will cause an increase of 0.884 in the compliance test of audit evidence.

H2: Big data analytics has a significant effect on the sufficiency of audit evidence.

Table 5(a): Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.926[a]	.858	.858	.43761
a. Predictors: (Constant), BDA: Application in Audit Evidence				
b. Dependent Variable: Audit Evidence: Sufficiency of Audit Evidence in BDA				

Table 5(b): ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	417.151	1	417.131	2178.313	.000[b]
	Residual	68.941	360	0.192		
	Total	486.091	361			
a. Dependent Variable: Audit Evidence: Sufficiency of Audit Evidence in BDA						
b. Predictors: (Constant), BDA: Application in Audit Evidence						

Table 5(c): Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.421	.085		4.948	.000
	BDA: Application in External Auditing	.901	.019	.926	46.672	.000
a. Dependent Variable: Audit evidence: Sufficiency of Audit Evidence in BDA						

Source: Authors' projection (2022)

According to Table no. 5(a), the coefficient of determination (R^2) is 0.858 which suggest that the application of BDA is responsible for 85.8% of the variation in sufficiency of audit evidence and the remaining 14.2% can be attributed to other factors not considered in this study.

The analysis of variance in Table no. 5(b) shows an F-value (1,360) of 2178.313 and a P-value of 0.000<0.05. Therefore, the second hypothesis is confirmed that states that BDA significantly affects sufficiency of audit evidence. Table no. 5(c) also shows that β1 = 0.926; t-value = 46.672 and p-value =0.000. This suggests a positive and significant impact of BDA on the sufficiency of audit evidence. In addition, it shows that a unit increase in BDAs will cause an increase of 0.926 in sufficiency of audit evidence.

H3: Big data analytics has a significant effect on the relevance and reliability of audit evidence.

Table 6(a): Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.942[a]	.888	.887	.38921
a. Predictors: (Constant), BDA: Application in Audit Evidence				
b. Dependent Variable: Audit Evidence: Relevance and Reliability of Audit Evidence in BDA				

Table 6(b): ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	431.557	1	431.557	2848.848	.000[b]
	Residual	54.534	360	.151		
	Total	486.091	361			
a. Dependent Variable: Audit Evidence: Relevance and Reliability of Audit Evidence in BDA						
b. Predictors: (Constant), BDA: Application in Audit Evidence						

Table 6(c): Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.227	.078		2.919	.000
	BDA: Application in Audit Evidence	.945	.018	.942	53.375	.000
a. Dependent Variable: Audit Evidence: Relevance and Reliability of Audit Evidence in BDA						

Source: Authors' projection (2022)

According to **Table no. 6(a)**, the coefficient of determination (R^2) is 0.888 and this suggests that 88.80% of the variation in relevance and reliability of audit evidence is caused by BDA, while 11.2% is due to other factors not considered in this study.

Table no. 6(b) reveals an F-value (1,360) of 2848.848 with a p-value of 0.000<0.05. This result indicates that the third hypothesis is confirmed, which states that BDA has a significant effect on the relevance and reliability of audit evidence. **Table no. 6(c)** reports the coefficient of the independent variable β_1 of 0.945, t-value of 53.375 and p-value of 0.000, suggesting a positive and significant impact of BDA onthe relevance and reliability of audit evidence. Moreover, a unit increase in BDA will cause a positive increase of 94.2% on relevance and reliability of audit evidence.

H4: Big data analytics has a significant effect on the assertions on financial statements.

Table 7(a): Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.726[a]	.528	.526	.79869
a. Predictors: (Constant), BDA: Application in Audit Evidence				
b. Dependent Variable: Audit Evidence: Assertion on Financial Statements in BDA.				

Table 7(b): ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	256.447	1	256.447	402.017	.000[b]
	Residual	229.644	360	.638		
	Total	486.091	361			

a. Dependent Variable: Audit Evidence: Assertion on Financial Statements in BDA

b. Predictors: (Constant), BDA: Application in Audit Evidence

Table 7(c): Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.096	.162		6.755	.000
	BDA: Application in Audit Evidence	.744	.037	.726	2.050	.000

a. Dependent Variable: Audit Evidence: Assertion on Financial Statements in BDA

Source: Authors' projection (2022)

According to Table no. 7(a), the coefficient of determination (R^2) is 0.528 and this suggests that 52.80% of the variation in assertions on financial statements is caused by BDA while 41.2% is due to other factors not considered in this study.

Table no. 7(b) reports results on the analysis of variance: F-value (1,360) = 402.017 with a p-value = 0.000<0.05. This result indicates that the regression model significantly predicts assertions on financial statements, and the fourth hypothesis is also confirmed.

Table no. 7(c) provides data on the coefficient of the independent variable: β_1 of 0.726, t-value of 20.050 and p-value of 0.000 and this translates to the fact that a unit increase in BDAs will cause a positive increase of 72.6% on assertions on financial statements.

4. Discussion on findings

The results of the analysis show that there is a substantial, significant and positive effect of BDA on control testing (R^2 = 0.781). These results provide empirical evidence to support the fact that the application of BDA tools by auditors to interrogate big data will enhance compliance tests and thereby improve audit evidence. The findings are consistent with the suggestions in Appelbaum *et al.* (2017, 6) and provide empirical evidence to support the requirement of PACOB 2018-005 (AS 1105 .03-08).

The study also shows that there is a substantial, significant and positive effect of BDAs on the sufficiency of audit evidence (R^2 = 0.858). Sufficient audit evidence can be obtained in big data database with the application of BDA. These empirical results are consistent with the literature reports (Eilifsen *et al.*, 2020, 42 and Balios *et al.* 2020, 214).

In addition, the results show that the application of BDA in audit evidence has a substantial, significant and positive effect on the relevance and reliability of audit evidence (R^2 = 0.888). This means that BDA has the capacity to enable auditors to obtain relevant and reliable audit evidence from big data. This aligns with the expectation of Appelbaum *et al.* (2017,6) and Balios *et al.* (2020, 214).

Finally, the use of BDA to interrogate financial statements is found to have a moderate (R^2 = 0.528), but significant and positive influence. This empirical evidence supports various qualitative studies on the effect of big data analytics on audit evidence (Appenbaum, 2016; Yadav, 2020; Salijeni*et al*, 2019).

5. Conclusion and further research

The results of this study showed that the implementation of BDA by auditors will enhance compliance and substantive tests by which appropriate, reliable and relevant evidence can be sought and obtained. It is therefore recommended that appropriate standards should be developed that will provide for the adoption of BDA tools in auditing-related services, specifying the process and the minimum benchmarks in term of clear objectives in accordance with the usual approach of the existing ISAs. In addition, appropriate in-house training should be organised for those involved in audit engagements by audit firms, while the Nigerian National University Commission, as well as other educational regulatory agencies elsewhere outside Nigeria, should make it mandatory for all tertiary institutions to introduce Big Data Analytics into their existing curricula.

It is suggested that further research should be carried out on big data analytics that will provide comparative findings from different settings, e.g., Europe, Asia, America or other African countries. Big 4 audit firms and accounting professional bodies should also initiate such studies to provide more comprehensive empirical evidence.

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