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Disruptive Technologies and Financial Reporting Quality of the Public Sector in Nigeria

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ABSTRACT

In recent times, the poor quality of financial reporting has given rise to inaccuracy, delay, non-transparency, poor accountability, and corruption. This study, therefore, examined the effect of disruptive technologies on the financial reporting quality of public firms in Nigeria. This study employed a survey research design. The population of this study comprised 43179 respondents from public firms in Nigeria. The sample size was 381, using a proportionate sampling technique. Data collected were analysed using both descriptive statistics and partial least squares-structured equation modelling. The study's findings showed that cloud computing and artificial intelligence have an insignificant positive effect on financial reporting quality. Big data analytics has a considerably favourable effect on financial reporting quality. By focusing on BDA while optimising AI and Cloud Computing adoption, the study concludes that firms can better leverage disruptive technologies to enhance financial reporting quality.

1. INTRODUCTION

For some time, the public sector has conventionally faced challenges related to the poor quality of financial reporting, including inaccuracy, delay, lack of transparency, poor accountability, and corruption (Abata & Suara, 2022). While this is not peculiar to advanced nations, through sound economic policies, debt management, fiscal planning, transparency, accountability, and advanced technological infrastructure, these nations have effectively managed their finances (World Bank, 2023).

This, however, is not the case in developing nations. According to a World Bank report, approximately 70% of low-income countries have weak public financial reporting systems, resulting in inadequate financial reporting and poor accountability (World Bank, 2021). Similarly, PEFA's 2020 assessments showed that only about 20% of low-income countries have effective financial reporting mechanisms, with most countries struggling with incomplete records and delayed financial reporting (PEFA, 2020).

In Africa, a 2021 report by the Auditor-General of South Africa revealed that 74% of municipalities did not comply with financial reporting standards, resulting in qualified, adverse, or disclaimed audit opinions. The 2018 report by the Nigerian Auditor-General indicated that over 80% of ministries, departments, and agencies faced issues with financial reporting, including unaccounted-for funds and incomplete records. According to Zibaghafa and Chukwu (2024), there is persistent corruption and inconsistent application of accounting standards in Nigeria that have undermined the quality of financial reporting, leading to loss of trust, poverty, and wastage. Even after the implementation of accrual-based IPSAS by some state governments, there still exists contention on the quality of financial reports (Beredugo,

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2021). While these have led to underdevelopment, the losses therein have been huge.

Conversely, these instances of nationwide poor-quality financial reports demonstrate the urgent necessity for a shift in the forms and processes of financial reporting of public organisations. An effective and strong financial reporting system is needed to improve the quality of financial reporting in Nigeria. According to Ahmad et al. (2024), there is a discernible relationship between the utilisation of modern accounting methodologies and the improvement of financial reports produced by governmental organisations. Consequently, the need for robust disruptive technologies in the financial reporting framework of the public sector has become urgently imperative.

The emergence of disruptive technologies, in recent times, has significantly impacted several areas, including the financial reporting system. In the public sector, digital technologies are considered a necessary direction of technical modernisation, improving the work of government agencies and their interaction with stakeholders (Pakhnenko & Kuan, 2023). These technologies, which include blockchain, artificial intelligence, robotic process automation, big data analytics, cloud computing, and the Internet of Things, are reshaping the landscape of financial reporting (Chowdhury et al., 2023).

Recent studies have shown the relationship between disruptive technologies and the quality of financial reporting. On the one hand, Odonkor et al. (2024) asserted that AI significantly improves the accuracy and efficiency of financial reporting. On the other hand, Kanaparthi (2024) suggested that disruptive technologies could revolutionise financial accounting by providing more precision and real-time financial reporting capabilities. Păvăloaia and Necula (2023) and Ahmad et al. (2024) asserted that the quality of financial reports could improve with the adoption of disruptive technologies. Although the importance and transformative potential of disruptive technologies have been established in literature, the process of how they manifest and their impact remain largely underexplored (Shahaab et al., 2023; Begkos et al., 2024). Based on this, this study examines the relationship between disruptive technology and financial reporting qualities in the Nigerian public sector.

Using empirical and literature analysis, this study investigates how disruptive technologies can transform financial reporting in the public sector, addressing crucial concerns while paving the way for dependable, transparent, and efficient financial reporting frameworks. By harnessing technological innovations, public sector firms can increase financial supervision, accountability, and public trust.

2. Literature Review

This section reviews extant literature to gauge the findings of scholars in relation to the effect of disruptive technologies on the quality of financial reporting in the public sector.

2.1 Conceptual Review

This section explores the conceptual framework of disruptive technologies and the quality of financial reporting.

2.1.1 Quality of Financial Reporting

Safkaur et al. (2019) described quality financial reports in the public sector as financial reports that can present reliable financial information. The definition focuses on the reliability and accuracy of information. However, it does not address the contextual relevance of the information provided. Abata and Suara (2022), on the other hand, defined financial reporting quality as the extent to which financial statements provide information that truthfully represents the financial position and performance of a firm. Such quality entails accuracy and reliability. While the emphasis on "truthful representation" is important, achieving complete and truthful representation is challenging due to limitations in data accuracy or reporting constraints.

Hribar et al. (2014) described the quality of financial reports as the degree of usefulness of the information contained therein. To make informed decisions, stakeholders like investors, regulators, and the public require high-quality financial reporting. However, the concept of "usefulness" is inherently subjective and can vary significantly among different stakeholders. While Zibaghafa and Chukwu (2024) opined that different measures can be used to assess the quality of financial reports, this study used faithful representation to explain the quality of financial reports.

2.1.1.1 Faithful Representation

Garg (2021) described faithful representation as the degree to which financial reports accurately reflect the economic transactions and conditions of an entity. It encompasses the completeness, neutrality, and freedom from error of the reported information. This highlights that faithful representation is crucial for ensuring a truthful depiction of an entity's financial situation. Non-compliance with this principle can lead to misleading information that adversely affects stakeholders' decision-making and trust.

Conversely, Adams and Haffar (2020) defined faithful representation as involving the presentation of financial information that is complete, neutral, and free from errors to enhance stakeholder confidence and trust in financial statements. However, the focus on ideal conditions may not fully account for the practical challenges of achieving faithful representation amidst diverse and evolving environments. Also, Falana et al. (2025) and Kogan (2022) defined faithful representation as the extent to which financial reporting accurately depicts the underlying economic realities of an entity amidst challenges such as evolving accounting standards and new financial technologies. However, the definition does not consider changes in accounting standards or financial practices. Based on this, the study defined faithful representation in financial reporting as the quality of financial information that accurately and completely reflects an entity's economic activities and conditions. It requires such information to be neutral, free from errors and provide a true and fair view of the entity's financial position and performance.

2.1.2 Disruptive technologies

Păvăloaia and Necula (2023) defined disruptive technology as the disruptive effects of new technologies within a domain. This entails new features that change a model, operation, or event. It represents innovations that fundamentally change existing industries or create entirely new markets by introducing revolutionary advancements in processes, products, or services. Its changed nature necessitated a break with established patterns. However, the definition focuses on the impact of technology without addressing the nature of the technology itself or its characteristics that make it disruptive. Smith (2022) described disruptive technology as an innovation that significantly alters the way consumers, industries, or businesses operate. However, the emphasis on altering operational methods may overlook other aspects of disruption, such as changes in market structure, regulatory impacts, or societal implications.

On the other hand, Bongomin et al. (2020) described disruptive technologies as technologies that have the potential to cause broader societal transformation by changing the existing economic sectors and tenets of work, production, and consumption. While the focus on broader societal transformation is valuable, the definition may be too broad, potentially including technologies that cause incremental rather than disruptive changes. Based on this, the main feature of disruptive technologies is a change in the status quo with a unique set of values that demands a new set of skills, knowledge, models, and context. In this regard, the study conceptualised disruptive technologies as technologies that change the status quo of an organisation's operations.

2.1.2.1 Artificial Intelligence

Zuiderwijk et al. (2021) described artificial intelligence as technological components that provide the capacity to process data and information in a way that entails intelligent behaviour. AI systems, which are composed of algorithms and models, possess abilities such as learning, planning, prediction, and control, enabling them to operate autonomously (UNESCO, 2020). Conversely, Wang et al. (2021) defined Artificial Intelligence (AI) as a system's ability to process data correctly, learn from such data, and use those learnings to achieve specific goals and tasks through flexible adaptation. Artificial intelligence is designed to simulate human intelligence, enabling systems to perform tasks like learning, reasoning, problem-solving, perception, and language understanding.

Ahmad et al. (2024) stated that the degree of logical thought and behaviour expression and the degree of similarity to human thought and behaviour differentiate artificial intelligence. The professional use of these resources—data, advanced analytical tools, state-of-the-art technology, and meticulous statistical analysis—to uncover undiscovered possibilities makes up artificial intelligence. Bharadiya (2023) stated that many businesses benefit greatly from artificial intelligence. While this is not limited to private organisations, this study conceptualised artificial intelligence as a system that performs tasks that are required in public sector organisations.

2.1.2.2 Big Data Analytics

As defined by VenkateswaraRao et al. (2023), Big data analytics refers to the procedure of analysing large amounts of information to learn about multiple industries as well as different companies. Big data analytics involves examining large and varied data sets to uncover hidden patterns, correlations, and insights that can inform business decisions. Thayyib et al. (2023), on the other hand, described big data analytics as the analysis of enormous datasets to derive actionable insights and value. Sivarajah et al. (2017) defined big data analytics as a phenomenon that analyses large volumes of data using sophisticated tools and techniques to extract valuable insights and solve business use cases.

Although big data analytics has been claimed to revolutionise the way firms operate and do business, Mikalef et al. (2021) stated that big data analytics entails the methodical examination of large datasets, which are complex and voluminous, to unearth valuable insights. Such valuable insights include hidden patterns, unknown correlations, customer preferences, and market trends. Gao and Sarwar (2022) asserted that big data analytics can enhance decision-making, improve customer experiences, optimise operations, and identify new revenue opportunities. Whether or not a user uses big data to make significant or well-informed decisions and has a big influence depends on the effectiveness of BDA (Thayyib et al., 2023). In this regard, this study conceptualised bid data analytics as an analytical tool employed to gain information from bid data.

2.1.2.3 Cloud Computing

Islam et al. (2023) defined cloud computing as consisting of networked elements providing services that are not managed individually by users. The service is provided over the internet on a pay-per-use basis. Oke et al. (2023), in this regard, asserted that cloud computing had been used in some sectors like banking, health and the construction industry. Conversely, Abd Al Ghaffar (2024) described cloud computing as the abstraction of hardware, software, networks, storage spaces and services used by system developers to execute complex processes and to provide those facilities through the internet to users.

Cloud computing enables providers to use distant data centres, storage and services for computing. Based on this, Ibrahim (2019) described cloud computing as a mature and stable technology and tool for commoditising computing resources. The benefits of migrating to the cloud in the public sector are considered to be flexibility, efficiency, resilience, cost-effectiveness, agility and scalability, sustainability, customer experience, and skills development (Brzozowska-Rup et al., 2024). Based on this, the study conceptualised cloud computing as the provision of services, storage and software facilities to users over the internet.

2.2 Theoretical Review

While the unified theory of acceptance and use of technology (UTAUT) forms the basis of this study's foundation, the study assessed the principles and assumptions of this theory to achieve its objectives.

Although this theory was first presented in 2003 by Viswanath Venkatesh, Gordon B. Davis, Fred D. Davis, and Michael G. Morris, it forms the theoretical basis of this study. This theory assumes that behavioural intentions are the primary predictors of actual technological use. According to the theory, behavioural intentions are influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions. In this regard. This theory uses a comprehensive model to explain the user's intentions to use information technology and subsequent usage behaviour.

On the one hand, Bajunaied et al. (2023) applied the principles of the Unified Theory of Acceptance and Use of Technology to investigate consumer behavioural intention towards FinTech services in Saudi Arabia. Again, Baptista et al. (2015) applied the theory's assumption to explain mobile banking services usage in Africa. Also, Shareef et al. (2011) used this theory to identify critical factors enabling citizens to adopt e-Government (e-Gov) at different service maturity stages. Conversely, Ayaz and Yanartaş (2020) applied it in determining the factors that influence the adoption and use of the Electronic Document Management System (EDMS) at Bartın University. A study by Akinnuwesi et al. (2022) used the UTAUT framework to establish factors that influence people's behavioural intention to accept digital tackling technologies.

Through a longitudinal study, UTAUT was found to explain approximately 50% of the variance in actual usage and 70% of the variance in behavioural intention to use (BI) (Venkatesh et al., 2003). Based on this, the UTAUT framework has been flexible to consolidate elements from eight different models while offering a more comprehensive understanding of technology acceptance. However, in terms of complexity and overemphasis on behavioural intentions, Bagozzi (2007) critiqued the UTAUT model, stating it had 41 variables for predicting intentions and 8 for behaviour, contributing to chaos in technology adoption studies. Behavioural intentions are not static, and specific contextual influences that could affect technology acceptance in different settings are overlooked (Dash et al., 2023).

2.3 Empirical Review

This study examined pertinent studies on disruptive technologies and the quality of financial reports in the public sector in line with the goals and assumptions that were developed for the study.

2.3.1 Artificial Intelligence and Financial Reporting Quality

The relationship between artificial intelligence and the quality of financial reports in the public sector relates to how a company's use of artificial intelligence facilities can affect the dependability, integrity, and correctness of its financial reporting. This relationship is critical to sustainability and financial reporting integrity. Based on this, Antwi et al. (2024) conducted a conceptual study on the relationship between financial reporting and AI. The study found that Artificial Intelligence (AI) technologies are revolutionising the financial reporting landscape by improving timeliness and accuracy. AI's contribution to financial reporting will grow as it develops, promoting efficiency, transparency, and accountability.

Moreover, Oyeniyi et al. (2024) explored the integration of Artificial Intelligence (AI) into financial reporting, focusing on its potential to enhance accuracy and timeliness. The study used qualitative research methodology to explore the evolution of financial reporting. Findings showed that AI significantly improves reporting accuracy but also presents ethical considerations, regulatory compliance, and potential biases. Elmegaard (2022), on the other hand, reviewed the literature on the impact of Artificial Intelligence on accounting, focusing on the current state of research from 2010 to 2021. The study proved that AI has a profound influence on accounting.

In the study conducted by Estep et al. (2023), the impact of AI on financial reporting quality in complex and subjective areas was examined. The study found that managers are uncertain about how auditors' use of AI will directly benefit their companies. The study also suggested that considering the effects of AI use by both companies and auditors was crucial when evaluating how AI influenced auditing and financial reporting. Also, Anantharaman et al. (2023) investigated the impact of AI adoption on financial reporting quality. It was found that AI technologies, such as machine learning and robotics, improved estimates and forecasting of business parameters. The adoption of AI has led to lower discretionary accruals and better mapping of cash flows. The study also found spillover benefits for audit quality.

Also, Adeyeri (2024) explored the impact of Artificial Intelligence (AI) on automating accounting processes and streamlining financial reporting. The study found that the benefits of AI in financial reporting include reduced manual errors, improved accuracy, and faster processing of financial transactions. Conversely, Odonkor et al. (2024) assessed the impact of Artificial Intelligence (AI) on traditional accounting practices, highlighting its role in financial reporting, auditing, and decision-making. With the use of peer-reviewed articles, case studies, and industry reports from the last decade, the study found that AI improved financial reporting accuracy and efficiency, automating routine tasks and enabling predictive analytics.

However, most of the studies reviewed lack a comprehensive overview of the nature and implications of artificial intelligence on financial reporting. While these studies used literature review approaches, the use of quantitative approaches to investigating the relationship between artificial intelligence and financial reporting has been underexplored. Based on this, the study hypothesised that:

H_{O1}: Artificial intelligence has no significant effect on the quality of financial reporting in the Nigerian public sector.

2.3.2 Big Data Analytics and Financial Reporting Quality

The use of big data analytics by a business can have an impact on the quality of its financial reporting. The relationship between big data analytics and the quality of financial reports in the public sector assumes some level of association. In this regard, Falana et al. (2023) investigated the impact of big data on accounting information quality in Nigerian firms. It focused on data volume, variety, and velocity, which affect accounting information. The study, involving 157 firms, found that data volume, variety, and velocity significantly affect accounting information.

On the one hand, Saleh et al. (2023) investigated the impact of BDA on financial reporting quality, as well as assessed the accounting challenges associated with Big Data. Using a qualitative approach, the study found the relevance of Big Data and BDA in affecting financial report quality and revealed that BDA had a significant effect on improving financial reporting quality. Big Data improved accounting, reporting, and expert judgment by providing professionals with. Conversely, Winoto et al. (2023) examined the impact of big data analytics on financial accounting in Indonesia using quantitative methods. The research used primary data from a questionnaire and SPSS 25. The results showed that big data analysis improves report quality, suggesting that using big data technology can enhance a company's financial performance.

On the other hand, Eleimat et al. (2023) explored the impact of big data on financial reporting quality in the industrial sector in Jordan. A field study with 325 financial managers revealed that big data dimensions positively affect financial reporting quality. Also, Ahmad et al. (2024) investigated the impact of accounting technology improvements on the generation of accurate financial reports in Jordan's public sector. The research used an ex-post facto survey methodology and a questionnaire, with 152 participants. The findings supported the growing importance of financial reporting in the global economic landscape and suggested the establishment of a comprehensive framework for enterprises' information technology infrastructure to reduce the risk of outdated technology overloading the public sector.

Moreover, Merhi and Bregu (2020) presented a holistic, flexible, and dynamic model for effective big data usage in the public sector. It used the analytic hierarchy process and three IS theories to evaluate factors. Technological advancements, data security, authentication, government focus, and transparency and accountability are key factors. The model confirmed previous literature findings and provided a framework for future studies. Practical implications include upgrading technologies, focusing on IT, and training users. Again, AlGhafri et al. (2024) explored the impact of digital transformation and big data on decision-making quality in Oman's public sector organisations. The research used a two-stage mixed-methods approach, including a literature review and a questionnaire. The findings revealed that relative advantage, complexity, and insecurity significantly predict technological decisions, while top management support, readiness, competitive pressure, and government regulations were significant environmental factors.

Previous research was based on literature reviews highlighting the likely impacts of big data analytics on the relevance of financial reports of the public sector. While the measures have been underexplored, recent peer-reviewed articles in the general accounting practice have not been exhaustive in describing how big data analytics impact financial reporting in the public sector. In line with these, it was hypothesised that:

HO2: Big data analytics has no significant effect on the quality of financial reporting in the Nigerian public sector.

2.3.3 Cloud Computing and Financial Reporting Quality

The adoption of cloud computing by a public sector corporation can affect the quality of its financial reporting. The relationship between big data analytics and the quality of financial reports in the public sector involves some level of connection. Based on this, Hasan et al. (2020) presented a comprehensive review of how cloud computing transforms financial decision-making in various domains and applications. These tools are transforming financial decision-making in various domains, enhancing real-time risk assessment, transactional efficiency, and predictive analytics. However, challenges like data security and integration complexities require further research. The future of data-driven financial services will be more integrated, responsive, and secure.

Also, Shakatreh et al. (2023) examined the impact of cloud computing on the quality of financial reports, involving 96 participants from ten commercial banks. Results showed that cloud computing and its characteristics significantly influence the quality of financial reports, mainly the comparability of financial reports, followed by reliability. Again, Almanaeseh et al. (2024) examined the impact of cloud technology implementation on Jordanian industrial businesses' financial statements. Results showed that cloud accounting significantly affects the quality of financial statements by dimension, especially the accuracy of financial statements.

On the one hand, Kmaleh (2023) investigated the impact of cloud computing on accounting information quality and its alignment with international financial reporting standards. The study used both theoretical and applied research methods, including file analysis and interviews with key stakeholders. Key findings suggest that cloud computing positively influences the quality and credibility of accounting information. On the other hand, Akai et al. (2023) examined the impact of cloud computing on financial reporting quality in Nigerian deposit money banks. The study used software as a service (Saas) and infrastructure as a service (IaaS) as proxies. The research used a survey design and a robust OLS regression analysis. Results showed that the software had a positive but insignificant effect on financial reporting quality, while the infrastructure had a significant and statistically positive effect.

Moreover, Musa (2024) investigated the impact of cloud computing and company size on accounting information quality, involving 178 respondents from Riyadh's accounting and audit offices. Results showed a positive relationship between perceived benefits and the quality of accounting information. Alqtish et al. (2021) studied the impact of cloud computing risks on accounting information quality from the perspectives of service providers and recipients. It found that human and legislative, material and cyber security significantly affect accounting information quality. However, there was no significant difference between recipients and service providers regarding risks. Olusola et al. (2024) assessed the impact of cloud accounting on the financial reporting quality of Nigerian deposit money banks. The research was conducted among 100 staff members in the IT Department and the internal control unit. The findings revealed that truthfulness is statistically insignificant in the quality of financial reporting. Furthermore, the findings revealed that usefulness has a significant difference in the quality of financial reporting.

Most of the constraints reviewed are reflected in the study sample. For instance, the studies of Olusola et al. (2024), Musa (2024), and Shakatreh et al. (2023) used 177, 178, and 96 respondents, respectively. This may affect the respective studies' findings in terms of generalisation and determine the extent to which CC services enhance the quality of financial reporting. Based on this gap, it was hypothesised that:

HO3: Cloud computing has no significant effect on the quality of financial reporting in the Nigerian public sector.

2.4 Conceptual Framework

Figure 1 depicts the interactions of the independent variable (disruptive technologies) with the dependent variable (quality of financial reporting).

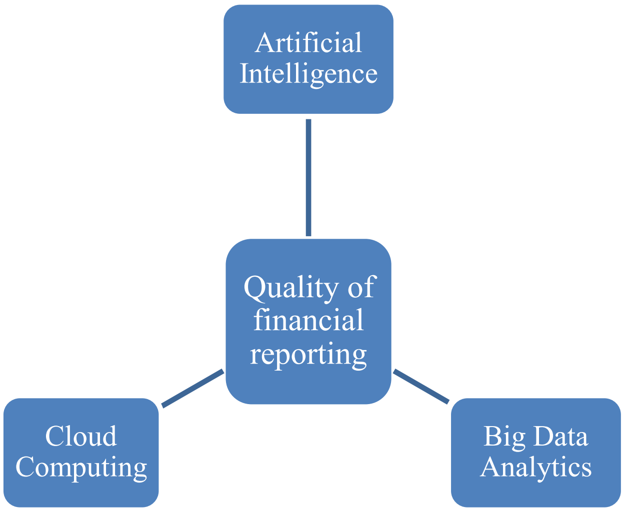

Fig. 1. Conceptual Framework

3. METHODOLOGY

3.1 Research Design

This study used a survey research design because it is well-suited to the study's objectives and the nature of the data being used. This approach enables systematic data collection from a specific population, ensuring a representative sample. Collecting data directly from respondents provides relevance and accuracy, while the use of a systematic questionnaire promotes consistency in data collection.

3.2 Source of Data

A carefully constructed questionnaire will be used to gather information from sources. In relation to the research objectives, the use of the most recent firsthand information will be obtained through this source.

3.3 Population of the study

The study population included 38382 respondents. These respondents were selected from the Central Bank of Nigeria (CBN), Nigeria Immigration Service (NIS), Federal Inland Revenue Service (FIRS), National Information Technology Development Agency (NITDA), Nigerian Communications Commission (NCC), Nigerian Customs Service (NCS), National Agency for Food and Drug Administration and Control (NAFDAC), National Health Insurance Scheme (NHIS), National Pension Commission (PenCom), Nigerian Electricity Regulatory Commission (NERC), Federal Road Safety Corps (FRSC), and Nigeria Customs Service (NCS). These agencies have embraced the use of disruptive technologies in their respective operations.

Table 1. Staff Population

S/N	Agency	Size
1	Nigerian Communications Commission (NCC)	798
2	National Information Technology Development Agency (NITDA)	813
3	Central Bank of Nigeria (CBN)	12951
4	National Agency for Food and Drug Administration and Control (NAFDAC)	3020
5	Federal Inland Revenue Service (FIRS)	9560
6	National Health Insurance Scheme (NHIS)	106
7	National Pension Commission (PenCom)	205
8	Nigerian Electricity Regulatory Commission (NERC)	310
9	Federal Road Safety Corps (FRSC)	7893
10	Nigeria Customs Service (NCS)	7523
	TOTAL	43179

Source: Authors' accumulation.

3.4 Sample size and Sampling techniques

Krejcie and Morgan's formula was used to calculate a sample size of 380 respondents. Proportionate sampling was used to distribute the sample across these agencies based on the relative proportion of the population. Consequently, the sample includes 7 from the Nigerian Communications Commission, 7 from the National Information Technology Development Agency (NITDA), 124 from the Central Bank of Nigeria, 30 from the National Agency for Food and Drug Administration and Control, 74 from the Federal Inland Revenue Service, 0 from National Health Insurance Scheme, 2 from National Pension Commission, 2 from Nigerian Electricity Regulatory Commission, 59 from Federal Road Safety Corps, and 74 Nigeria Customs Service.

According to Krejcie and Morgan (1970), the sample size is calculated as follows:

$$S = \frac{X^2 N\,P\,(1-P)}{d^2(N-2)+X^2 P\,(1-P)} \qquad (1)$$

Where:

S = required sample size

X^2 = the table value of chi-square for 1 degree of freedom at the desired confidence level (3.841 for 95% confidence level)

N = population size

P = population proportion (assumed to be 0.5 for maximum sample size)

d = degree of accuracy (the margin of error, e.g., 0.05 for ±5%)

The sample size is, therefore, 381

Table 2. Sample Size

S/N	Agency	Size
1	Nigerian Communications Commission (NCC)	7
2	National Information Technology Development Agency (NITDA)	7
3	Central Bank of Nigeria (CBN)	114
4	National Agency for Food and Drug Administration and Control (NAFDAC)	27
5	Federal Inland Revenue Service (FIRS)	84
6	National Health Insurance Scheme (NHIS)	1
7	National Pension Commission (PenCom)	2
8	Nigerian Electricity Regulatory Commission (NERC)	3

9	Federal Road Safety Corps (FRSC)	70
10	Nigeria Customs Service (NCS)	66
	TOTAL	381

Source: Authors' accumulation.

3.5 Research Instrument

The study will collect data through a structured, closed-ended questionnaire. The questionnaire will be designed to assess the extent to which ministries, development, and agencies have adopted the use of disruptive technologies in financial reporting and how it has impacted their operations. The questionnaire will be drafted using a five-point Likert scale. The questionnaire will include two sections (A & B). Section A will contain the respondents' background information, while Section B will contain questions about the use of disruptive technologies and their impact on financial reporting.

3.6 Reliability and validity of the research instrument

Table 3a summarises the constructs' reliability and validity for Artificial Intelligence. AITG1, AITG2, AITG3, AITG4, and AITG5 are indicators used to assess the construct (artificial intelligence). Factor loadings measure the association between each indicator and the latent construct, with greater absolute values (above 0.5) indicating a stronger link. In this scenario, AITG1 (0.494) and AITG2 (0.496) are slightly below the desirable 0.5 level. AITG3 of 0.747 has a high factor loading, indicating a positive association with the AI construct. AITG4 of -0.226 indicates a weak or inverse association with the concept. AITG5 (0.125) does not contribute much to the construct. However, a composite reliability of 1.000 indicates perfect reliability, which is unusually high. The average variance extracted (AVE) of 1.000 also indicates that the construct explains a significant portion of the variance in its indicators. AITG5 (0.125) makes minimal contributions to the construct. The average variance extracted (AVE) of 1.000 shows that the construct accounts for a considerable share of the variance in its indicators.

In Table 3b, the concept of Big Data Analytics is measured by five indicators, although only BDAY2 (0.627) and BDAY5 (0.759) have sufficiently high factor loadings to be considered reliable. BDAY1 and BDAY4 have very low or negative loadings, whereas BDAY3 has a weak loading, indicating that they do not contribute significantly. The composite reliability (0.685) is slightly below the optimum threshold of 0.7, indicating potential internal consistency issues. However, the AVE (0.526) is adequate, indicating that the construct explains a reasonable amount of variation in its indicators, albeit not very strongly.

In Table 3c, cloud computing is evaluated using five indicators. Nevertheless, only CCMP1 (0.623) and CCMP4 (0.601) have appropriate factor loading. The remaining indicators, particularly CCMP2 (-0.405), CCMP3 (0.013), and CCMP5 (0.259), have low or negative loadings. This indicates that they do not contribute much to the construct. The composite reliability (1.000) and AVE (1.000) are abnormally perfect, suggesting an issue with the data or model calculation.

Table 3d displays financial reporting quality validity results. This is measured using five indicators, but only FRQ2 (0.685) and FRQ3 (0.641) exhibit strong factor loadings, making them reliable contributors. FRQ1 (0.473) shows a moderate loading, but FRQ4 (0.305) and FRQ5 (0.055) are weak indicators. The composite reliability of 0.695 suggests moderate internal consistency. The AVE of 0.535 indicates that the construct explains an acceptable amount of variance in the indicators.

Table 3a. Reliability and Validity for Artificial Intelligence

Variables	Indicator	Factor	Reliability	Average Variance	Item
Artificial Intelligence	AITG1	0.494			2
	AITG2	0.496			
	AITG3	0.747			
	AITG4	-0.226			
	AITG5	0.125	1.000	1.000	

Source: Authors' accumulation.

Table 3b. Reliability and Validity for Big Data Analytics

Variables	Indicators	Factor	Reliability	Average Variance	No of Items
Big Data Analytics	BDAY1	-0.070			2
	BDAY2	0.627			
	BDAY3	0.383			
	BDAY4	-0.024			
	BDAY5	0.759	0.685	0.526	

Source: Authors' accumulation.

Table 3c. Reliability and Validity for Cloud Computing

Variables	Indicator	Factor	reliability	Average Variance	Items
Cloud Computing	CCMP1	0.623			1
	CCMP2	-0.405			
	CCMP3	0.013			
	CCMP4	0.601			
	CCMP5	0.259	1.000	1.000	

Source: Authors' accumulation.

Table 3d. Reliability and Validity for Financial Reporting Quality

Variables	Indicator	Factor	Reliability	Average Variance	Items
Financial Reporting Quality.	FRQ1	0.473			2
	FRQ2	0.685			
	FRQ3	0.641	0.695	0.535	

FRQ4	0.305
FRQ5	0.055

Source: Authors' accumulation.

The findings of the discriminant validity, which is determined by taking the square root of the AVE in each latent variable and using the Fornell-Larcker Criterion, are shown in Table 4. To avoid multicollinearity problems, this test is crucial for validating the extent to which measures of distinct qualities are unrelated to one another. The study variables' discriminant validity analysis is displayed in Table 7. The inter-construct correlation coefficients between AI and BDA, CCO, and FRQ are 0.085, -0.010, and 0.12, respectively. The square root of the AVE of AI is 1.000. This suggests a strong discriminant validity. Furthermore, 0.725 is the diagonal value for Big Data Analytics (BDA). Being higher than the correlations of other variables, this number exhibits excellent discriminant validity. It is implied that BDA is different from the other components.

Once more, CCO has a diagonal value of 1.000. This suggests strong discriminant validity because it outweighs all of its correlations with other components. FRQ has discriminant validity, as confirmed by the square root of AVE being bigger than its correlations with Artificial Intelligence (0.121), Big Data Analytics (0.227), and Cloud Computing (0.063). For every construct, discriminant validity has been demonstrated. Artificial Intelligence, Big Data Analytics, Cloud Computing, and Financial Reporting Quality are different components of the model.

Table 4. Discriminant Validity

Study Variables	Artificial Intelligence	Big Data Analytics	Cloud Computing	Reporting Quality
Artificial Intelligence	1.000			
Big Data Analytics	0.085	0.725		
Cloud Computing	-0.010	0.129	1.000	
Financial Reporting Quality	0.121	0.227	0.063	0.732

Source: Authors' accumulation.

3.7 Model Specification

The econometric model used in this study adheres to the framework provided by Zibaghafa and Chukwu (2024) to investigate the relationship between the independent and dependent variables. It is organised as follows:

$$QFP = \beta_0 + \beta_1 AI_{it} + \beta_2 BDA_{it} + \beta_3 CCO_{it} + \varepsilon_{it} \quad (2)$$

Where:

QFP = Quality of Financial Performance

AI = Artificial Intelligence

BDA = Big Data Analytics

CCO = Cloud Computing

ε_{it} = Error Term

β_0 = Intercept

β_1, β_2, β_3 = The Coefficients of the independent variable

The *a-priori* expectation = β_1, β_2, $\beta_3 > 0$, which implies that a positive correlation is anticipated between the explanatory variables and the dependent variable.

3.8 Data Analysis Techniques

To analyse data, this study used descriptive statistics (mean, median, variance, standard deviation, skewness, and kurtosis) and inferential statistics (regression analysis, correlational analysis, and so on).

4. Data Analysis And Discussion Of Findings

This section displays the analysis's findings as well as their ramifications.

4.1 Data Presentation

Table 5 shows descriptive statistics in percentages and frequencies based on the respondents' backgrounds. There were 381 respondents. A total of 188 respondents were female, accounting for 49.4% of the sample. There were 193 male respondents, who accounted for 50.66% of the sample. 11.55% of the sample, or 44 respondents, worked as accountants. Of the respondents, 42 individuals worked as principal accountants, accounting for 11.02%. The surveyor, GIS analyst, procurement specialist, and administrative officer each had a single respondent. Other significant roles include Chief Accountants (9.97%), Assistant Admin Managers (9.71%), and Regional Accountants (8.14%). Some roles are sparsely represented, such as Business Entrepreneurs (0.52%), CEOs (0.26%), Head Reengineering (0.26%), and Project Managers (0.26%).

However, respondents have varying years of service. Some respondents have been in service for under 5 years. This accounts for 22.31% of the total respondents. While 20.73% of the respondents have 11-15 years and 6-10 years of experience, 20.47% of the respondents have served for 16-20 years. 15.75% of respondents have over 26 years of experience. The distribution of respondents is well spread across different levels of service experience, with more respondents falling into early-to-mid career categories (below 20 years of service).

In terms of years of experience in disruptive technology, respondents have varying levels of experience with disruptive technologies. 85 respondents, representing 23.88% of the sample, have below 1 year of experience. 79 of the respondents, which accounts for 23.36% of the sample, have 1-3 years, while 24.15% of the respondents have 4-5 years. 3.94% have above 5 years, while 24.67% have above 6 years of experience. This suggests that a majority of respondents have between 1 to 6 years of experience with disruptive technologies.

Table 5. Demographic Information of Respondents

Demographic Information	Frequency	Percentages	Cumulative
Gender			
Female	188	49.34	49.34
Male	193	50.66	100
Total	381	100	

Post/Designation			
Account executive	29	7.61	7.61
Accountant	44	11.55	19.16
Assistant Admin Manager	37	9.71	28.87
Business entrepreneur	2	0.52	29.4
CEO	1	0.26	29.66
Chief Accountant	38	9.97	39.63
Director	39	10.24	49.87
Financial Analyst	29	7.61	57.48
Head Reengineering	1	0.26	57.74
Manager	27	7.09	64.83
Principal Accountant	42	11.02	75.85
Project manager	1	0.26	76.12
Regional Accountant	31	8.14	84.25
Senior Account Officer	29	7.64	91.6
Total	381	100	
Years in Service			
Below 5 years	85	22.31	22.31
Between 11-15 years	79	20.73	43.04
Between 16-20 years	78	20.47	63.52
Between 6-10 years	79	20.73	84.25
Above 26 years 60	15.75	100	15.75
Total	381	100	
Years of Experience in Disruptive Technology			
Below 1 year	91	23.88	23.88
Between 1-3years	89	23.36	47.24
Between 4-5years	92	24.15	71.39
above 5 years	15	3.94	75.33
Above 6 years	94	24.67	100
Total	381	100	

Source: Authors' accumulation.

4.1 Descriptive Statistics

Table 6 presents the descriptive information for financial reporting quality (FRQ), artificial intelligence (AI), big data analytics (BDA), and cloud computing (CCMP). With 38 observations for each variable, the sample size is consistent across the measurements. FRQ has a mean size of 3.1102. This implies that respondents rated the quality of financial reporting as moderately high. The standard deviation of FRQ is 1.3272, which suggests a narrow spread. About 42.67% of the variability is related to the mean, or 0.4267%. The skewness value of -0.1215 indicates near-zero skewness, indicating roughly symmetrical answers. 1.8781 has a Kurtosis of less than 3, which suggests a platykurtic distribution.

Once more, the respondents' average AI response was 3.1364, indicating that respondents agreed with the questions posed. This indicates that respondents generally had less favourable opinions of artificial intelligence. The data distribution results show a minor variation in answers when compared to the mean value, as indicated by the standard deviation of 1.3444. 42.86% is the coefficient of variation, having a minimum of 1 and a maximum of 5. This indicates that the respondents' range of responses to the question was limited. There are 1195 responses to the artificial intelligence questions. With a skewness of -0.1975 and a kurtosis of 1.8770, the responses displayed an irregular and negatively skewed distribution, suggesting that they were not normally distributed.

Furthermore, BDA has an average value of 2.9658. This implies that the respondents' opinions of big data analytics were not favourable. The 1.3884 standard deviation, on the other hand, varied slightly from the mean value. A constant variation of 46.81% is seen. Only 1130 respondents answered in the negative for Big Data Analytics. It has a skewness of 0.0078. Given that more responses indicate higher values for data mining analytics, this suggests a slight positive skew. For data mining analytics, a platykurtic distribution is indicated by a Kurtosis of 1.7358.

In a similar vein, 2.9396 is the average response from the respondents on cloud computing. This indicates that most respondents disagreed with the questions that were asked. The value of the standard deviation is 1.3234. This suggests that there is minimal variation between respondents' responses to cloud computing and the mean value. The variance in relation to the mean, measured by a coefficient of variation, is approximately 45.02%. 1120 responses have been received for cloud computing. With a kurtosis score of 1.8807 and a skewness of 0.0495, the responses showed a positively skewed distribution, suggesting that they were not normally distributed. With low mean scores and higher variability, the respondents' overall perceptions of all variables are generally less positive.

Table 6. Descriptive Statistics of Study Variables

Variables	FRQ	AITG	BBDAY	CCMP
OBS	381	381	381	381
Mean	3.1102	3.1102	3.1364	2.9658
S.D.	1.3272	1.3272	1.3444	1.3884
C.V	0.4267	0.4267	0.4286	0.4681
Min	1	1	1	1
Max	5	5	5	5
Sum	1185	1185	1195	1130
Skewness	-0.1215	-0.1975	0.0078	0.0495
Kurtosis	1.8781	1.877	1.7358	1.8807

Source: Authors' accumulation.

4.2 Correlation Analysis

Table 7 presents Spearman's rho correlation coefficients between financial reporting quality (FRQ), artificial intelligence (AI), big data analytics (BDA), and cloud computing (CCO). The relationship between financial reporting quality (FRQ) and artificial intelligence (AI) has a correlation coefficient of 0.0385, with a p-value of 0.4538. This is a weak positive correlation, but it is not statistically significant ($p > 0.05$). This implies that there is no meaningful relationship between FRQ and AI based on this data. The correlation coefficient FRQ with BDA is 0.1078 with a p-value of 0.0354. This is a small but insignificant positive correlation. This indicates a small but meaningful relationship between FRQ and BDA. As Big Data Analytics usage increases, Financial Reporting Quality slightly improves. Also, the correlation coefficient of FRQ with CCO is -0.0565, with a p-value of 0.2710. This shows a weak but insignificant negative correlation. Thus, there is no significant relationship between FRQ and CCO.

The correlation between Artificial Intelligence (AI) and Big Data Analytics (BDA) is 0.0190 with a p-value of 0.7116. This shows a very weak but insignificant positive correlation. This indicates no meaningful relationship between AI and BDA. Also, the correlation between AI and CCO is -0.0076, with a p-value of 0.0000. This shows a very weak but significant negative relationship between AI and CCMP. The correlation coefficient between Data Analytics (BDA) and Cloud Computing (CCO) is 0.0511, with a p-value of 0.3195. While this relationship is insignificant, this is a weak positive correlation. Therefore, there is no meaningful relationship between BDA and CCO.

Table 7. Correlation of the Study Variables

Variables	**Spearman's rho**	**Financial Reporting Quality**	**Artificial Intelligence**	**Big Data Analytics**	**Cloud Computing**
Financial Reporting Quality	Coefficient	1.000			
	Sig. (2-tailed)	-			
Artificial Intelligence	Coefficient	0.0385 0.4538	1.000		
	Sig. (2-tailed)		-		
Big Data Analytics	Coefficient	0.1078* 0.0354	0.0190	1.000	
	Sig. (2-tailed)		0.7116	-	
Cloud Computing	Coefficient	-0.0565 0.2710	-0.0076	0.0511 0.3195	1.000
	Sig. (2-tailed)		0.0000		-

Source: Authors' accumulation.

4.3 Disruptive Technologies and Financial Reporting Quality in Selected Public Entities in Nigeria.

Table 8 summarises the structural model results showing the impact of disruptive technologies (Artificial Intelligence, Big Data Analytics, Cloud Computing) on Financial Reporting Quality. Both R-squared (R^2) and R-squared adjusted explain the variance in the dependent variable. Therefore, the R-Square of 0.063 and R-Square Adjusted of 0.056 indicate that the model explains 6.3% of the variance in Financial Reporting Quality. This suggests that disruptive technologies contribute only modestly to explaining financial reporting quality. The Q^2, which shows the predictive relevance, is 0.036. While the Q^2 value is above 0, this suggests that the model has some predictive relevance.

The path coefficients, together with a p-value of artificial intelligence and financial reporting quality, are 0.103 and 0.162 respectively. This implies that the effect of Artificial Intelligence on financial reporting quality is positive but weak and not statistically significant ($p > 0.05$). AI usage does not significantly influence financial reporting quality in this model. The effect size of Artificial Intelligence is 0.011, which indicates the effect size of AI on Financial Reporting Quality is very small. However, this finding negates the findings of studies conducted by Antwi et al. (2024), Oyeniyi et al. (2024), Elmegaard (2022), Adeyeri (2024) and Odonkor et al. (2024).

Also, the path coefficients of Big Data Analytics and Financial Reporting Quality, together with a p-value, are 0.214 and 0.000 respectively. This indicates that Big Data Analytics has a positive and significant effect on financial reporting quality. This implies that BDA significantly improves financial reporting quality. The effect size of Big Data Analytics is 0.048. This implies that the effect size of BDA is small but more substantial. This finding conforms with the findings of Falana et al. (2023), Saleh et al. (2023), Winoto et al. (2023) and Eleimat et al. (2023). It is also consistent with the assumptions of the Unified Theory of Acceptance and Use of Technology**.**

Moreover, the path coefficient of cloud computing and financial reporting quality is 0.037, with a p-value of 0.514. This implies that the impact of cloud computing on financial reporting quality is positive but insignificantly weak. Thus, cloud computing does not significantly affect financial reporting quality in this model. The effect size of cloud computing is 0.001. This indicates that the effect size of cloud computing is negligible, indicating almost no impact on financial reporting quality.

In general, Big Data Analytics has the most significant and positive impact on financial reporting quality, suggesting that organisations using BDA are likely to experience improvements in their financial reporting. Artificial Intelligence and Cloud Computing show weak, non-significant effects on financial reporting quality. This finding does not conform to the findings of Hasan et al. (2020) and Shakatreh et al. (2023). This finding agrees with the finding of Olusola et al. (2024).

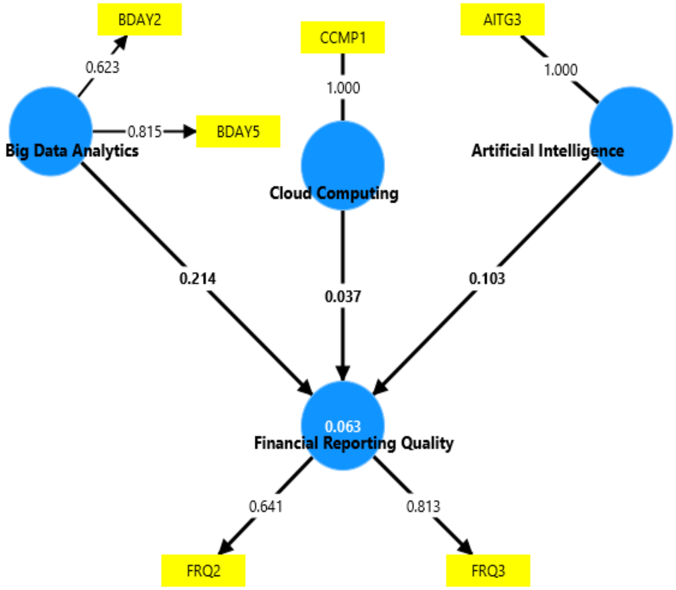

Fig. 2. Partial Least Squares Structural Equation Modelling Showing the Effect of Disruptive Technologies on Public Sector Financial Reporting Quality

Table 8. Effect of Disruptive Technologies on Financial Reporting Quality

Constructs	Path Co-efficient	T-Statistic	P-values
Artificial Intelligence -> Financial Reporting Quality	0.103	1.398	0.162
Big Data Analytics -> Financial Reporting Quality	0.214	3.906	0.000
Cloud Computing -> Financial Reporting Quality	0.037	0.653	0.514
R Square	0.063		
R Square Adjusted	0.056		
Q^2	0.036		
F-Square (Effect Size)- Artificial Intelligence	0.011		
F-Square (Effect Size)- Big Data Analytics	0.048		
F-Square (Effect Size)- Cloud Computing	0.001		
F-Square (Effect Size)- Artificial Intelligence	0.011		
SRMR	0.142		
NFL	-4.745		
RMSE	0.986		

Source: Authors' accumulation.

4.4 Discussion of Findings

The path analysis shows that artificial intelligence influences financial reporting quality. This suggests that, while not statistically significant, artificial intelligence has a positive impact on financial reporting quality. This model shows that the use of AI has no substantial impact on financial reporting quality. This result contrasts with previous research, such as that of Antwi et al. (2024), Oyeniyi et al. (2024), and Adeyeri (2024), who found more significant effects of AI on financial reporting. AI is continually evolving, and while it has great potential, its current use may be hampered by factors such as the requirement for significant investments, technological adaptation obstacles, or a lack of experienced individuals to efficiently apply AI systems in financial reporting.

Furthermore, the results of the analysis carried out show that Big Data Analytics has a favourable and significant impact on financial reporting quality. This means that BDA greatly enhances financial reporting quality. The significant effect of BDA on FRQ is consistent with previous research findings by Falana et al. (2023), Saleh et al. (2023), and Eleimat et al. (2023), all of which have highlighted the role of BDA in improving decision-making processes, reducing errors, and improving the overall accuracy and timeliness of financial reporting. BDA improves business insights by efficiently analysing large financial data, enhancing reporting quality, real-time analysis, early anomaly detection, and increased transparency, as demonstrated in this study.

Again, cloud computing does not have a meaningful effect on financial reporting quality. This means that the influence of cloud computing on financial reporting quality is good but not statistically significant. Thus, cloud computing has no substantial impact on financial reporting quality in this paradigm. This result differs from previous research by Hasan et al. (2020) and Shakatreh et al. (2023), who discovered a more significant favourable impact of Cloud Computing on financial reporting processes. The minor findings in this model could be ascribed to the present use of Cloud Computing, which may prioritise storage solutions over improving the real accuracy of financial reporting. Cloud computing's potential in FRQ may also be determined by how well it integrates with other reporting technologies, such as AI and BDA.

5. Conclusion and Recommendation

The study's findings illustrate the divergent effects of disruptive technologies—Artificial Intelligence (AI), Big Data Analytics (BDA), and Cloud Computing—on Financial Reporting Quality (FRQ). While the study examined the effect of disruptive technologies on the financial reporting quality in the public sector in Nigeria, literature on disruptive technologies and financial reporting quality was evaluated. Data was gathered from 381 respondents using a survey design. These data were examined using partial least squares structural equation modelling. The investigation showed that cloud computing and artificial intelligence have an insignificant positive impact on financial reporting quality. This implies that the current usage of AI and cloud computing in financial reporting may be limited or not yet fully optimised for improving the quality of financial reports. Big data analytics has a considerable favourable impact on financial reporting quality, suggesting that its adoption leads to measurable improvements in financial reporting quality.

Based on this, the following recommendations were made. Firstly, public agencies should focus on Big Data Analytics (BDA) for immediate improvement. Given that BDA has had the most positive influence on financial reporting quality, public agencies should prioritise its adoption and investments in BDA tools and infrastructure. This can increase data accuracy, transparency, and decision-making, resulting in better financial reporting quality. Secondly, public agencies should improve AI integration in Financial Reporting. While the study discovered that AI does not yet have a substantial impact on FRQ, its potential is enormous. Public sector agencies should look at more advanced AI applications for financial reporting, such as automating difficult accounting processes, detecting fraud, and performing predictive analytics. Thirdly, public agencies should reassess the function of Cloud Computing in Financial Reporting. Because Cloud Computing has a minor impact, its function in financial reporting may be underutilised. Organisations should seek greater cloud integration with BDA and AI to boost data accessibility, collaboration, and real-time reporting.

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