GUSAU JOURNAL OF BUSINESS ADMINISTRATION (GUJOBA)

Vol. 5 Issue 1, June, 2026; Pp 267 - 287

ISSN: 2811-1702. https://doi.org/10.57233/gujoba.v5i1.24

A Publication of the Department of Business Administration, Federal University Gusau, Nigeria

CRITICAL ENVIRONMENTAL SUCCESS FACTORS AND BIG DATA ANALYTICS ADOPTION OF SELECTED QUOTED DEPOSIT MONEY BANKS IN NIGERIA

***Joseph AZAGE and Omorodion OMOREGBE**
Department of Business Administration, Faculty of Management Sciences, University of Benin, Benin City, Edo State, Nigeria.

*Correspondence: azagejoseph@gmail.com

ABSTRACT

This study examined the effect of performance management and succession planning on organisational change in NNPC Exploration & Production Limited. The study was motivated by the need for organisations in the oil and gas sector to remain adaptable in response to rapid technological changes, regulatory demands, and competitive pressures. A survey research design was adopted, and data were collected from employees using a structured questionnaire. A total of 325 questionnaires were administered, out of which 292 were valid for analysis, representing an 89.8% response rate. Data were analysed using descriptive statistics and inferential techniques. The findings revealed that performance management practices have a significant positive effect on organisational change, indicating that effective goal setting, feedback, and appraisal systems enhance organisational responsiveness to change. Similarly, succession planning was found to have a significant relationship with organisational change, suggesting that leadership continuity and talent development improve organisational stability and transformation capacity. The study concludes that performance management and succession planning are key determinants of organisational change in NNPC E&P. The study recommends strengthening performance systems, enhancing succession planning frameworks, and integrating modern HR analytics to improve change outcomes.

Keywords: Big Data Analytics Adoption, Competitive Pressure, External Support, Government Regulations, Environmental Factors, Deposit Money Banks

1. INTRODUCTION

The rapid expansion of digital data has transformed industries globally, compelling organisations to process vast amounts of structured and unstructured data daily. Big Data Analytics (BDA) has become a crucial tool for extracting insights, optimising operations, and enhancing customer experiences (Seseni & Mbohwa, 2021). The banking sector, in particular, has increasingly recognised BDA's potential to improve financial innovation, customer centricity, and overall performance (Bonsu, 2024; Phan & Tran, 2022). Studies indicate that BDA adoption enhances operational efficiency and competitive positioning in banking institutions worldwide (Fatima et al., 2024; Diniz et al., 2018; Nobanee et al., 2021).

Environmental factors play a critical role in shaping BDA adoption. Competitive pressure is a key driver, pushing banks to embrace data-driven decision-making for improved service delivery, product innovation, and operational efficiency (Maroufkhani et al., 2022; Ferraris et al., 2019). Research suggests that banks leveraging big data capabilities can enhance profitability and market agility (Aziz, Long, & Wan Hussain, 2023), while those failing to integrate BDA risk losing market share to technologically advanced competitors (Raguseo & Vitari, 2018; McIntyre, 2018). The influence of

competitive pressure on BDA adoption has been widely observed in emerging economies, where digital transformation is increasingly shaping financial services (Verma & Bhattacharyya, 2017).

External support, including technological infrastructure, industry expertise, and partnerships, also influences BDA adoption. Handling large datasets requires significant investment in technology and skilled personnel, often facilitated by collaborations with fintech firms, academic institutions, and regulatory bodies (Haleem et al., 2020; Maroufkhani, Wan Ismail, & Ghobakhloo, 2020). Studies indicate that partnerships with fintech firms enable banks to leverage cloud-based big data solutions, improving efficiency and decision-making (Ajimoko, 2018; Coleman et al., 2016). Additionally, the availability of supportive digital ecosystems and government-backed digitalisation policies enhances the feasibility of BDA adoption (Owusu et al., 2020; Lateef & Keikhosrokiani, 2023).

It has also been noted that government regulations of a country can further shape BDA adoption, especially when they establish legal and compliance frameworks that influence data governance and cybersecurity practices (European Commission, 2018; Nasrollahi & Ramezani, 2020). While strict regulations can increase compliance costs and limit data accessibility, they also protect against fraud, data breaches, and unethical data usage (Gualtieri, 2012; Hasan, Popp, & Oláh, 2020). Research suggests that well-structured data privacy regulations can improve consumer trust and encourage banks to adopt responsible BDA practices (Truong, 2022; Park & Kim, 2021). However, balancing regulatory requirements with innovation remains a key challenge for Nigerian banks, as regulatory ambiguity often leads to hesitancy in technology adoption (PwC, 2013).

BDA adoption in Nigerian banks involves integrating big data technologies to enhance decision-making, operational efficiency, and customer engagement. Successful implementation includes deploying machine learning for fraud detection, predictive analytics for risk assessment, and customer segmentation for personalised banking experiences (Mikalef & Krogstie, 2020; Sun et al., 2014). Studies on big data adoption in financial institutions suggest that data maturity and organisational readiness significantly impact the success of BDA initiatives (Grimaldi et al., 2019; Singh et al., 2022). However, in Nigeria, adoption remains inconsistent due to factors such as infrastructure readiness, organisational culture, and data governance frameworks (Raguseo & Vitari, 2018; Nasrollahi & Ramezani, 2020).

The Nigerian banking sector sits at the intersection of rapid technological evolution and increasing regulatory scrutiny (Ajimoko, 2018; Rogers, 1993). While many banks acknowledge BDA's strategic benefits, external constraints, including inadequate infrastructure, skills shortages, and regulatory ambiguities, often hinder implementation (Gangwar, 2018; Sivarajah et al., 2017). Additionally, research suggests that Nigerian banks face challenges in scaling big data initiatives due to insufficient digital transformation policies (Camarinha-Matos et al., 2019; Ramezani & Camarinha-Matos, 2019). This study examined these environmental success factors and their role in facilitating or hindering BDA integration in Nigerian banks.

The increasing reliance on Big Data Analytics (BDA) in global banking highlights its potential to drive operational efficiency, enhance customer satisfaction, and promote financial inclusion. However, BDA adoption in Nigeria remains underexplored, particularly regarding the environmental determinants that influence this process. While prior research has focused on technological infrastructure, organisational readiness, and internal capabilities (Braganza et al., 2017; Hung, He & Shen, 2020), there is a significant gap in understanding the external environmental forces shaping BDA adoption in Nigeria's banking sector. This gap is critical due to Nigeria's unique challenges, including regulatory ambiguities, competition, and external support structures, which can either facilitate or hinder adoption.

A notable gap in the literature is the geographical bias in existing studies. Most research on BDA adoption has concentrated on developed economies, with limited exploration of the challenges faced by banks in developing economies like Nigeria (Verma & Bhattacharyya, 2017). As Agrawal (2015) notes, infrastructural limitations, regulatory inconsistencies, and technological barriers unique to developing economies necessitate targeted investigations. Additionally, the scarcity of empirical studies on the Nigerian banking sector complicates the generalisation of findings from developed economies, making this study crucial for examining environmental success factors influencing BDA adoption in Nigeria.

Furthermore, the literature predominantly emphasises firm-specific factors, overlooking broader environmental determinants in BDA adoption. While organisational readiness, technological capabilities, and perceived benefits have been explored (Maroufkhani et al., 2022), limited research has addressed how competitive pressure, external support, and government regulations shape the adoption process (Gupte, 2018; Haleem et al., 2020). In Nigeria's evolving financial landscape, banks face pressure to integrate advanced analytics to enhance service delivery, yet the role of external factors such as partnerships with fintech firms and technology providers remains underexplored. This study seeks to fill this gap by evaluating how these external environmental factors influence BDA adoption in Nigerian banks.

Another overlooked aspect in the literature is the empirical evidence on the interplay between government regulations and BDA adoption in Nigeria. While regulatory policies aim to improve data governance and cybersecurity, overly stringent regulations may stifle innovation (Lai, Sun & Ren, 2018). Nigerian banks face a complex regulatory framework requiring a balance between compliance and strategic objectives. However, the impact of these regulations on BDA adoption remains underexplored.

Empirical studies offer insights into these dynamics. Egwuonwu et al. (2023) highlight the role of technological, organisational, and external factors in shaping BDA adoption in Nigeria, although their findings suggest insignificant effects of competitive pressure and regulatory factors. Fatima et al. (2024) identify the mediating role of BDA adoption in enhancing bank performance through environmental, organisational, and technological factors. Similarly, Bonsu (2024) demonstrates a positive relationship between BDA, financial innovation, and performance. Maroufkhani et al. (2020) affirm the importance of the Technology-Organisation-Environment (TOE) framework, showing that technological, organisational, and environmental factors significantly influence BDA adoption. This study aims to address these gaps by investigating critical environmental success factors influencing BDA adoption in Nigerian banks.

The broad objective of this study is to examine the influence of critical environmental success factors on Big Data Analytics (BDA) adoption among selected quoted deposit money banks in Nigeria. Specifically, the study seeks to: evaluate the influence of competitive pressure and Big Data Analytics adoption among selected quoted deposit money banks in Nigeria; to analyse the influence of external support and Big Data Analytics adoption among selected quoted deposit money banks in Nigeria; and to investigate the influence of government regulations and Big Data Analytics adoption among selected quoted deposit money banks in Nigeria.

2. LITERATURE REVIEW

2.1 Conceptual Review

Big Data Analytics Adoption

Big Data refers to large, complex, and rapidly growing datasets that traditional data management tools struggle to process. It is defined by the "3Vs", volume, velocity, and variety, with additional attributes such as veracity, value, and variability highlighting concerns about data quality and complexity (Laney, 2001; Sivarajah et al., 2017; Ghasemaghaei, 2018). The rise of digital transformation has exponentially increased data generation from social media, transactional records, and IoT devices, necessitating advanced analytics for meaningful insights (Wang et al., 2021; Verma & Bhattacharyya, 2017).

Big Data comprises three core components: storage, processing, and governance. Scalable storage solutions such as cloud computing and distributed databases enable efficient data management (Abuljadail et al., 2023; Nobanee et al., 2021). However, data security and privacy have become critical, particularly with stringent regulations such as the General Data Protection Regulation (GDPR), which requires robust governance strategies (European Commission, 2018; Phan & Tran, 2022). Organisations must balance innovation with compliance, ensuring secure and ethical data use (Li et al., 2022; Ramezani & Camarinha-Matos, 2019).

Big Data drives innovation and competitive advantage across industries. In finance, it enhances fraud detection, risk assessment, and customer personalisation (Fatima et al., 2024; Hasan, Popp, & Oláh, 2020). In healthcare, predictive analytics improves patient outcomes and operational efficiency (Bonsu, 2024; Maroufkhani et al., 2020). The integration of artificial intelligence (AI) and machine learning (ML) further extends data-driven decision-making capabilities, unlocking new applications and efficiencies (Mikalef et al., 2019; Grimaldi et al., 2019). As industries increasingly

leverage Big Data, organisations must navigate technological, regulatory, and ethical challenges to harness its full potential for sustainable growth and innovation (Frisk & Bannister, 2017; Turner, Schroeck, & Shockley, 2013).

Big Data Analytics

Big Data Analytics (BDA) involves using advanced techniques like machine learning, artificial intelligence (AI), and predictive modelling to extract actionable insights from vast datasets (Wamba et al., 2017). Unlike traditional methods, BDA allows real-time data processing, enabling businesses to make more accurate and efficient data-driven decisions (Arias-Pérez et al., 2022; Ghasemaghaei, 2018). This capability has revolutionised industries, particularly in finance, where BDA supports risk assessment, fraud detection, and personalised banking services (Sun et al., 2014; Fatima et al., 2024). In supply chain management, BDA improves demand forecasting, logistics planning, and inventory control (Tiwari, Wee, & Daryanto, 2018; Lai, Sun, & Ren, 2018).

The value of BDA lies in its ability to uncover hidden patterns in large datasets, leading to improved operational efficiency, customer targeting, and strategic decision-making (Kościelniak & Puto, 2015; Ferraris et al., 2019). Companies integrating BDA with business intelligence (BI) solutions enhance their decision-making and competitive agility (Owusu et al., 2020; Seseni & Mbohwa, 2021). However, challenges such as data privacy concerns, technical complexities, and the need for skilled professionals limit its widespread adoption (Belhadi et al., 2019; Maroufkhani et al., 2023). Furthermore, BDA implementation requires substantial investment in infrastructure, data governance, and regulatory compliance (Nasrollahi & Ramezani, 2020; Hasan, Popp, & Oláh, 2020).

Many industries, such as banking, telecommunications, and e-commerce, actively invest in BDA to gain a competitive edge (Hung et al., 2020; Diniz et al., 2018). The integration of cloud computing, edge computing, and blockchain technologies is enhancing BDA's scalability and security, further expanding its applications (Camarinha-Matos et al., 2019; Lateef & Keikhosrokiani, 2023).

Big Data Analytics Adoption

The adoption of Big Data Analytics (BDA) has become a strategic priority for organisations aiming to leverage data-driven decision-making. In the banking sector, BDA is crucial for fraud detection, credit risk evaluation, and customer relationship management (Tiwari et al., 2018; Sun et al., 2014). Factors such as technological readiness, organisational support, and external regulatory pressures determine BDA adoption (Mikalef et al., 2018; Wang & Wang, 2023). Larger financial institutions with robust IT infrastructure are more likely to adopt BDA than smaller banks that face resource constraints (Gupta & George, 2016). Integrating BDA enhances decision-making capabilities and operational agility, particularly in regulated sectors like banking and finance (Grimaldi, 2020; Ferraris et al., 2019).

Government regulations play a key role in shaping BDA adoption, acting as both enablers and barriers. Supportive policies, such as tax incentives and clear data privacy laws, encourage investment in BDA (Rahman & Iverson, 2015; Raguseo & Vitari, 2018). In contrast, stringent or unclear regulations can hinder adoption, increasing compliance burdens and operational uncertainties, especially in developing economies (Wamba et al., 2017). For instance, Nigeria's Central Bank has introduced cybersecurity frameworks and data protection guidelines, which guide BDA adoption in the banking sector (PwC, 2013). However, frequent regulatory chasnges and complex compliance processes may deter smaller firms from fully embracing BDA (Ghobakhloo et al., 2012).

The benefits of successful BDA adoption include enhanced business intelligence, improved customer experiences, and increased profitability (Lim, 2016; Wamba et al., 2017). Conversely, failure to adopt or improperly implement BDA can lead to missed opportunities, increased operational risks, and reduced competitiveness (Chen et al., 2012; Raguseo & Vitari, 2018). As digital transformation progresses, organisations must prioritise investments in BDA to stay competitive in a rapidly evolving landscape (Sivarajah et al., 2017).

Critical Environmental Success Factors

Critical Environmental Success Factors (CESFs) refer to external conditions, forces, and influences within an organisation's operating environment that significantly affect its ability to achieve strategic objectives and sustain competitive performance. These factors originate

outside the organisation and shape managerial decisions, organisational capabilities, and the adoption of innovations. CESFs are regarded as critical because they create opportunities or constraints that determine the success of organisational initiatives, particularly those involving technological transformation and digital innovation (Maroufkhani et al., 2019; Ramezani & Camarinha-Matos, 2019). In increasingly volatile and technology-driven markets, organisations must continuously monitor and respond to environmental conditions to maintain relevance, competitiveness, and operational effectiveness (Fosso Wamba et al., 2015; Hasan, Popp, & Oláh, 2020).

The concept of CESFs encompasses a broad range of environmental dimensions, including regulatory frameworks, competitive intensity, technological developments, economic conditions, industry dynamics, and external stakeholder support (Gatali et al., 2016; Nobanee et al., 2021). These factors influence organisational behaviour by shaping the context within which strategic decisions are made. Unlike internal organisational resources and capabilities, environmental success factors are generally beyond direct managerial control. Consequently, organisations must adopt adaptive strategies and develop responsive capabilities to manage environmental uncertainties and exploit emerging opportunities (Saltz & Shamshurin, 2016; Ghasemaghaei, 2018). The ability to recognise and respond effectively to environmental signals often determines whether organisations successfully implement strategic initiatives or experience performance setbacks.

Within the context of Big Data Analytics (BDA) adoption, CESFs play a particularly important role because the implementation of advanced analytical technologies is heavily influenced by environmental conditions. Competitive pressure encourages organisations to adopt BDA solutions to improve decision-making, operational efficiency, customer insights, and market responsiveness. As competitors increasingly utilise data-driven strategies, organisations may perceive BDA adoption as essential for sustaining competitive advantage (Ferraris et al., 2019; Raguseo & Vitari, 2018). Government regulations also influence adoption by establishing compliance requirements, data governance standards, cybersecurity obligations, and privacy protections that either facilitate or constrain technology implementation (Fatima et al., 2024; Phan & Tran, 2022). Furthermore, external support in the form of vendor expertise, technical assistance, consultancy services, and digital infrastructure provides organisations with the resources required to overcome implementation challenges and maximise the benefits of analytics technologies, particularly in developing economies characterised by technological limitations (Egwuonwu et al., 2023; Owusu et al., 2020).

The strategic management of CESFs enables organisations to align their technological investments with environmental realities, thereby reducing uncertainty and enhancing organisational performance. Organisations that proactively respond to regulatory developments, leverage external expertise, and anticipate competitive changes are better positioned to innovate and sustain long-term growth (Brock & Khan, 2017; Truong, 2022). Conversely, failure to recognise and adapt to critical environmental conditions may result in implementation failures, compliance risks, reduced competitiveness, and strategic inefficiencies (Gangwar, 2018; Singh et al., 2022). Therefore, integrating CESFs into organisational planning and decision-making processes is essential for promoting resilience, facilitating technology adoption, and achieving sustainable competitive advantage in an increasingly data-driven business environment (Belhadi et al., 2019; Seseni & Mbohwa, 2021; Lateef & Keikhosrokiani, 2023).

Competitive Pressure

Competitive pressure refers to the degree of influence exerted by rivals, market forces, and industry competition on an organisation's strategic decisions and operational activities. It arises when organisations are compelled to improve products, services, processes, or technological capabilities in response to actions taken by competitors or changing market expectations. As a critical environmental success factor, competitive pressure serves as an external stimulus that encourages organisations to pursue innovation, enhance efficiency, and strengthen their market position to sustain competitiveness and organisational performance (Maroufkhani et al., 2019; Phan & Tran, 2022). In increasingly dynamic business environments characterised by digital transformation and rapid technological change, competitive pressure has become a major determinant of organisational adaptation and strategic renewal (Raguseo & Vitari, 2018; Grimaldi et al., 2019).

The concept of competitive pressure is rooted in the notion that organisations operate within competitive markets where survival and growth depend on their ability to respond effectively to external challenges. Competitive pressure may arise from direct industry rivalry, threats posed by new entrants, the availability of substitute products and services, or increasing customer expectations regarding quality, speed, innovation, and value delivery (Porter, 2008; Gatali et al., 2016). The emergence of digital technologies and data-driven business models has further intensified competition by lowering market barriers, accelerating innovation cycles, and enabling firms to differentiate themselves through superior customer experiences and operational excellence (Gao, Koronios, & Selle, 2015; Soubra, 2021). Consequently, organisations increasingly view technological innovation as a strategic necessity rather than a discretionary investment.

Within the context of Big Data Analytics (BDA) adoption, competitive pressure is widely recognised as a significant driver of technological innovation. Organisations adopt BDA to improve strategic decision-making, enhance customer relationship management, optimise operational processes, identify emerging market opportunities, and achieve sustainable competitive advantage (Fatima et al., 2024; Truong, 2022). As competitors increasingly utilise advanced analytics to generate insights and improve performance, organisations face mounting pressure to invest in similar technologies to avoid competitive disadvantage. Empirical studies indicate that firms operating in highly competitive environments are more likely to adopt BDA because of the perceived strategic benefits associated with data-driven decision-making and innovation (Wamba et al., 2015; Egwuonwu et al., 2023). This relationship is particularly evident in industries where information quality, speed of decision-making, and customer responsiveness significantly influence organisational success.

In the Nigerian banking sector, competitive pressure has emerged as a major catalyst for BDA adoption. The increasing presence of digital banking platforms, financial technology firms, and technology-driven financial services has intensified competition among banks, compelling them to leverage analytics capabilities to improve efficiency and customer value. Banks increasingly utilise BDA for fraud detection, credit risk assessment, customer segmentation, personalised financial services, and predictive decision-making to maintain market relevance and enhance competitiveness (Gopalakrishnan et al., 2012; Hasan, Popp, & Oláh, 2020). Nevertheless, while competitive pressure can stimulate innovation and organisational learning, excessive competitive intensity may result in resource constraints, rushed technology investments, and strategic misalignment if adoption decisions are not supported by adequate organisational capabilities and planning (Saltz & Shamshurin, 2016; Belhadi et al., 2019). Therefore, organisations that effectively manage competitive pressure are better positioned to exploit technological opportunities, strengthen market positioning, and achieve superior performance in an increasingly data-driven economy (Owusu et al., 2020; Nasrollahi & Ramezani, 2020; Maroufkhani et al., 2023; Ramezani & Camarinha-Matos, 2019).

External Support

In today's business landscape, external support is a vital Critical Environmental Success Factor (CESF) that facilitates organisational growth, innovation, and technology adoption. It encompasses assistance from technology vendors, consultants, government agencies, and financial institutions, helping firms navigate expertise gaps, infrastructure limitations, and financial constraints (Ghasemaghaei, 2018; Maroufkhani et al., 2020). This support is especially crucial in industries undergoing rapid technological change, where firms must adopt Big Data Analytics (BDA), cloud computing, and enterprise resource planning (ERP) systems to remain competitive (Ghobakhloo et al., 2012; Nasrollahi & Ramezani, 2020).

External support manifests in four key areas: technical assistance (expertise in system integration), training and skill development (enhancing workforce competencies), financial support (grants, investment funding), and regulatory facilitation (favourable policies and incentives) (Wang & Wang, 2023; Diniz et al., 2018). These components collectively enhance an organisation's ability to adopt and maximise emerging technologies, particularly in resource-limited environments (Owusu et al., 2020).

The impact of external support varies by industry and geography. In the financial sector, banks and fintech firms in developing economies rely on technology vendors to deploy advanced analytics, with those having strong external partnerships achieving higher adoption

success (Fatima et al., 2024; Raguseo & Vitari, 2018). Similarly, SMEs benefit from cloud-based solutions and third-party expertise to overcome financial and technical barriers (Bonsu, 2024; Maroufkhani et al., 2023). However, reliance on external support depends on organisational readiness, vendor credibility, and economic conditions (Ghobakhloo et al., 2012; Gatali et al., 2016).

While external support bridges knowledge and resource gaps, excessive dependence may lead to risks such as vendor lock-in and diminished internal capabilities (Grimaldi, 2020; Sun et al., 2014). A balanced approach, leveraging external expertise while strengthening internal capacities, ensures sustained innovation and competitiveness (Frisk & Bannister, 2017; Camarinha-Matos et al., 2019).

Government Regulations

Government regulations are fundamental to shaping organisational strategies, operational frameworks, and technology adoption. As a Critical Environmental Success Factor (CESF), they encompass laws, policies, and compliance mandates that ensure business activities adhere to legal, ethical, and security standards (Nasrollahi & Ramezani, 2020; Sivarajah et al., 2017). These regulations influence sectors such as financial reporting, consumer rights, data privacy, and digital governance, particularly impacting emerging technologies like Big Data Analytics (BDA), cloud computing, and artificial intelligence (AI) (Wamba et al., 2017; Lateef & Keikhosrokiani, 2023).

Government regulations comprise legislative frameworks (e.g., cybersecurity laws, financial reporting requirements), institutional oversight (regulatory agencies like central banks), and compliance mechanisms (rules, reporting standards, and penalties) (Park & Kim, 2021; Nobanee et al., 2021). In the financial sector, regulations such as Anti-Money Laundering (AML) and Know Your Customer (KYC) drive BDA adoption for fraud detection and identity verification (Wang & Wang, 2023; Fatima et al., 2024).

The influence of government regulations on technology adoption is twofold. Supportive policies, such as tax reliefs and data governance standards, enhance digital transformation by reducing uncertainty (Owusu et al., 2020; Maroufkhani et al., 2023). Conversely, restrictive or ambiguous regulations may deter investment due to compliance risks, high costs, or bureaucratic inefficiencies (Grimaldi, 2020; Hasan, Popp, & Oláh, 2020). Regulatory volatility further discourages long-term digital investments, especially among SMEs (Ghobakhloo et al., 2012; Truong, 2022).

Effective regulations foster trust, security, and responsible data usage, especially in sensitive industries like banking and healthcare (Phan & Tran, 2022; Gupte, 2018). However, excessive regulatory burdens can stifle innovation and increase operational costs. A balanced regulatory approach, harmonising compliance with technological advancement, is key to sustainable growth (Mikalef et al., 2019; Ramezani & Camarinha-Matos, 2019).

Firms that proactively engage with regulators and integrate compliance into digital strategies gain competitive resilience, whereas non-compliance risks legal and reputational consequences (Egwuonwu et al., 2023; Soubra, 2021). A proactive regulatory strategy is essential for navigating evolving business landscapes (Wamba et al., 2017; Park & Kim, 2021).

2.2 Theoretical Framework

This study is anchored primarily on the Technology-Organisation-Environment (TOE) Framework, complemented by Institutional Theory and Resource Dependence Theory. The integration of these theories provides a comprehensive explanation of how environmental factors are associated with the adoption of Big Data Analytics (BDA) among selected quoted deposit money banks in Nigeria. The combined theoretical perspective is particularly relevant because the study focuses on environmental success factors, namely Competitive Pressure, External Support, and Government Regulations, which represent critical external conditions shaping organisational technology adoption decisions.

The Technology-Organisation-Environment (TOE) Framework developed by Tornatzky and Fleischer (1990) serves as the principal theoretical foundation of the study. The framework posits that organisational technology adoption is influenced by technological, organisational, and environmental contexts. Since the present study focuses specifically on environmental determinants of BDA adoption, the environmental dimension of the TOE Framework provides the overarching structure for explaining how external

conditions influence adoption decisions within the banking sector. The framework suggests that organisations respond to environmental opportunities and constraints when evaluating the adoption of technological innovations such as Big Data Analytics.

Institutional Theory further strengthens the explanation by emphasising the role of external institutional pressures in shaping organisational behaviour. According to DiMaggio and Powell (1983), organisations often adopt practices and technologies to achieve legitimacy, maintain competitiveness, and conform to environmental expectations. Within the context of this study, Competitive Pressure reflects mimetic isomorphism, whereby banks imitate successful competitors that utilise Big Data Analytics to enhance operational efficiency, customer experience, and strategic decision-making. Similarly, Government Regulations reflect coercive isomorphism because banks are required to comply with directives, standards, and regulatory requirements imposed by agencies such as the Central Bank of Nigeria, the Nigeria Deposit Insurance Corporation, and data protection authorities. Consequently, competitive and regulatory pressures create institutional incentives that encourage BDA adoption.

Resource Dependence Theory provides an additional explanation for the role of External Support in technology adoption. The theory argues that organisations depend on external actors for critical resources necessary for survival and competitiveness. In the context of Big Data Analytics adoption, banks frequently rely on technology vendors, consultants, cloud service providers, industry associations, and strategic partners for specialised expertise, infrastructure, implementation support, and technical knowledge. Access to these external resources reduces uncertainty and enhances organisational capability to adopt and utilise advanced analytics technologies effectively. Therefore, external support represents an important resource acquisition mechanism that facilitates successful BDA adoption.

The integration of the TOE Framework, Institutional Theory, and Resource Dependence Theory provides a coherent theoretical basis for understanding how environmental success factors are associated with Big Data Analytics adoption among selected quoted deposit money banks in Nigeria. While the TOE Framework explains the environmental context within which adoption occurs, Institutional Theory clarifies the influence of competitive and regulatory pressures, and Resource Dependence Theory explains the importance of external support and resource acquisition. Together, these theories provide a robust foundation for interpreting the empirical findings of the study.

Theoretical Mapping of Study Variables

Variable	Theory	Explanation
Competitive Pressure	Institutional Theory	Represents mimetic isomorphism, whereby banks adopt Big Data Analytics to remain competitive and emulate successful industry peers.
Government Regulations	Institutional Theory	Represents coercive isomorphism, whereby banks adopt Big Data Analytics to comply with regulatory requirements, data governance standards, and supervisory expectations.
External Support	Resource Dependence Theory	Represents resource acquisition through access to technological expertise, infrastructure, vendor support, and strategic partnerships.
Environmental Context	TOE Framework	Represents the environmental dimension influencing organisational technology adoption decisions.

Source: Researchers' Conceptualisation Based on Tornatzky and Fleischer (1990), DiMaggio and Powell (1983), and Pfeffer and Salancik (1978).

2.3 Empirical Review

Bonsu (2024) examined the impact of Big Data and financial innovation on financial performance in the UK banking sector using a mixed-methods approach. The study found that Big Data enhances financial innovation, which in turn drives superior financial outcomes. A quantitative analysis based on survey data from 150 bank managers revealed a positive relationship between Big Data, financial innovation, and performance. Cross-country comparisons confirmed that long-term investments in Big Data and financial innovation contribute to sustained financial performance. Qualitative interviews with thirteen bank managers explored the adoption of customer data, revealing that technological, organisational, and environmental factors influence the adoption process, with customer data

recognised as a key driver of financial innovation and competitive advantage.

Egwuonwu, Mendy, and Oruh (2023) investigated the drivers of Big Data Analytics (BDA) adoption in Nigeria's manufacturing and service industries, examining its implications for decision-making and organisational performance. Survey data from 261 professionals were analysed using business-to-business marketing, dynamic capabilities theory, and the Technology-Organisation-Environment (TOE) framework. The findings indicated that organisational value, technological competence, top management support, and organisational readiness positively influence BDA adoption. Competitive pressure, external support, and regulatory factors were identified as drivers, although competitive pressure and regulatory environment had insignificant direct effects. The study also found that BDA adoption enhances management's policy decisions and improves financial and non-financial performance. BDA investments, although costly, contribute to business productivity, innovation, and long-term profitability, offering critical insights for policymakers and industry leaders.

Gupte (2018) explored the critical success factors (CSFs) in Big Data projects, identifying key determinants of project success. A survey of Big Data professionals revealed that business-driven objectives, iterative execution, adherence to project management processes, and leveraging tool capabilities significantly enhance project success. These findings offer a structured approach to improve Big Data project execution, highlighting the importance of effective methodologies in ensuring successful project implementation.

Fatima, Malik, Ayub, and Ellahi (2024) examined the impact of technological, organisational, and environmental factors on BDA adoption within Pakistan's financial sector. The study employed a quantitative research methodology and found that these factors significantly influence BDA adoption, which, in turn, positively impacts bank performance. While BDA adoption mediated the relationship between these factors and performance, no significant moderating effect was found for analytics capability and strategic alignment. The study offers practical implications for bank management and policymakers, particularly regarding the enhancement of analytics capabilities and strategic alignment in the banking sector.

Lateef and Keikhosrokiani (2022) focused on the critical success factors influencing the adoption of business intelligence (BI) in SMEs in Lagos State, Nigeria. Data analysis from 165 employees revealed that knowledge management, technological orientation, market intelligence, and entrepreneurial orientation significantly impacted business intelligence implementation. However, organisational resources, management structure, and culture had insignificant effects. This research provides valuable insights into the determinants of business intelligence adoption, emphasising its role in decision-making, economic growth, innovation, and performance improvement, aligning with Sustainable Development Goals (SDGs) 8 and 9.

Maroufkhani et al. (2020) explored the factors influencing BDA adoption in small and medium-sized enterprises (SMEs) in Iran. The study identified key determinants, including complexity, uncertainty, security concerns, trialability, top management support, organisational readiness, and external support. The findings highlighted the significant impact of BDA adoption on marketing and financial performance, offering valuable insights for managers to develop effective strategies for successful BDA implementation and for service providers to promote adoption among SMEs.

Ajimoko (2018) examined the criteria guiding small business enterprises (SBEs) in adopting cloud-based Big Data Analytics (CBBDA). Using a qualitative approach with semi-structured interviews of 20 IT professionals from 10 SBEs, the study identified internal and external adoption criteria. Internal factors included technology/organisation alignment, financial standing, and management support, while external factors involved vendor-related and environmental considerations. The study highlighted that lack of top management support could hinder CBBDA adoption, despite its potential benefits.

Owusu et al. (2020) investigated the critical success factors influencing the adoption of cloud-based business intelligence (Cloud BI) in SMEs in Ghana. The study found that top management support, skilled human resources, and technological resources were the primary factors influencing Cloud BI adoption. The research also revealed that Cloud BI in SMEs was primarily used for communication and data storage, offering benefits like secure and cost-effective data sharing across multiple branches.

Maroufkhani, Wan Ismail, and Ghobakhloo (2020) proposed a unified model for BDA adoption in SMEs, integrating the Technology-Organisation-Environment (TOE) framework and the Resource-Based View (RBV). The study found that technological and organisational factors were the most influential determinants of BDA adoption in SMEs. BDA adoption significantly mediated the relationship between technological, organisational, and environmental factors and SMEs' performance, enhancing both financial and market performance. This research provides a framework for SMEs, highlighting the importance of these factors in the adoption of BDA and encouraging SMEs to embrace this technology to improve operations.

3. METHODOLOGY

The survey research design was adopted to explore the critical environmental success factors influencing the adoption of Big Data Analytics (BDA) within the Nigerian banking sector. This design was deemed appropriate as it facilitated the collection of primary data from respondents, enabling the researcher to understand the relationships between competitive pressure, external support, government regulations, and BDA adoption. Given the cross-sectional nature of the study, it can be noted that the findings indicate associations among variables rather than definitive causal relationships.

This study focuses on employees in key departments involved in or influenced by Big Data Analytics in five major Nigerian banks: First Bank of Nigeria, United Bank for Africa (UBA), Guaranty Trust Bank (GTBank), Access Bank, and Zenith Bank. These banks were selected for their large asset base, customer deposits, loan portfolio, market capitalisation, and international operations. They are industry leaders in digital transformation, particularly in Big Data Analytics, AI, and automation, and are subject to strict regulatory oversight by the Central Bank of Nigeria (CBN), Nigeria Deposit Insurance Corporation (NDIC), and Financial Reporting Council of Nigeria (FRCN). A purposive sampling technique was used to select 350 respondents from critical departments such as Technology & Data Management, Risk & Compliance, Strategic & Operational Units, Human Capital Management, and Digital & Customer Channels. These departments were chosen for their direct involvement in or influence on Big Data Analytics adoption. It is important to note that Human Capital Management was included because successful BDA adoption requires workforce planning, analytics competency development, digital skills acquisition, change management, and employee readiness. Human resource professionals play a central role in developing the human capabilities necessary for analytics implementation and organisational transformation. The population of 591 employees was identified from official Human Resource databases obtained from the selected banks. Following the purposive selection of the five banks, proportionate stratified random sampling was employed. Staff lists obtained from each department constituted the sampling frame, and respondents were randomly selected within each departmental stratum using random number procedures. This ensured that every eligible employee within the selected departments had an equal probability of selection (Coosie & Field, 2009). The distribution of the sample among the banks is shown in Table 2.

Table 1: Study Population Proportion

S/N	Banks	Number of Staff in Selected Departments at the Head Office of the Selected Banks					Total No.
		Technology & Data Management	Human Capital Management	Strategic & Operational Units	Risk & Compliance	Digital & Customer Channels	N
1	Access Bank	20	15	18	12	35	**100**
2	First Bank	28	32	22	27	28	**137**
3	GT Bank	18	30	27	18	30	**123**
4	UBA	22	32	18	14	38	**124**

5	Zenith Bank	25	27	12	13	30	**107**
	TOTAL	**113**	**136**	**97**	**84**	**161**	**591**

(*Source: Human Resources Department Database of the Banks, 2025*)

Table 2: Proportionate Distribution of sample among the selected banks using the formula

S/N	BANK	N
1.	Access Bank	59
2.	First Bank	81
3.	GT Bank	73
4.	UBA	74
5.	Zenith Bank	63
	Total	**350**

Source: Researchers' Computation, 2025

Primary data were collected using a structured questionnaire divided into two sections. Section A gathered socio-demographic information about the respondents, such as age, gender, education, and professional experience. Section B consisted of close-ended questions designed to assess environmental factors, focusing on competitive pressure, external support, and government regulations, and their perceived influence on BDA adoption. Questions were also asked on BDA adoption.

The research instrument was validated for face and content validity by experts in IT, management, and senior academics. A pilot study with 35 respondents tested its reliability, leading to refinements for clarity. Cronbach's Alpha was applied, yielding a reliability coefficient of 0.78, indicating strong internal consistency. The reliability statistics are summarized in Table 3.

Table 3: Summary of Cronbach's Alpha Reliability Coefficients

Variables	Cronbach's Alpha Co-efficient	Items
Competitive Pressure	0.81	5
External Support	0.83	5
Government Regulations	0.85	5
Big Data Analytics Adoption	0.87	5
Overall Average Alpha for the instrument (α)	**0.84**	**25**

Source: Researchers' Computation, 2025.

Data Collection Procedure

Data were collected over a three-month period in 2024. A combination of online and offline methods were used to administer the questionnaires to the respondents. Both methods aimed to reach a diverse pool of participants across the selected banks in Lagos. The respondents were assured of confidentiality, and informed consent was obtained before data collection began.

Model Specification

The study's model was specified with BDA adoption (BDAA) as the dependent variable and critical environmental factors as the independent variables. The model was functionally specified in the equation below as:

$$BDAA = f(CP, ES, GR) \dots\dots\dots\dots\dots\dots\dots\dots\dots 3.1$$

Econometrically, the model equation is stated as: $$BDAA = \beta_0 + \beta_1 CP + \beta_2 ES + \beta_3 GR + \varepsilon. 3.2$$

Where: β_0 = Constant; β_1 to β_3 = Coefficients of the independent variables; BDAA: Big Data Analytics Adoption; CP: Competitive Pressure; ES: External Support; GR: Government Regulations

With our *Apriori* expectation stated as:

$$\beta_1, \beta_2, and\ \beta_3 > 0 \dots\dots\dots 3.3$$

This implies that an increase in competitive pressure, external support, and government regulations positively influences BDA adoption. It should be noted that no control variables such as bank size, respondent experience, educational level, or tenure were included in the regression model because the study focused specifically on examining the relationships between environmental success factors and BDA adoption.

Descriptive statistics (means, standard deviations, frequencies) were used to summarise the data. To test the hypotheses, multiple regression analysis was performed, examining the relationships between competitive pressure, external support, government regulations, and

Big Data Analytics adoption. All tests were conducted at a 5% level of significance using SPSS version 24.

4. RESULTS AND DISCUSSION

Data Presentation, Analysis and Interpretation

This section presents and analyses data on the Critical Environmental Success Factors for Big Data Analytics (BDA) Adoption in the Nigerian Banking Sector. The analysis involves descriptive statistics, correlation analysis, and Ordinary Least Squares (OLS) regression to examine the influence of environmental factors on BDA adoption.

Socio-Demographic Characteristics of Respondents

Table 4 presents the demographic distribution of respondents based on gender, age, educational qualification, job role, and years of experience in the banking sector.

Table 4: Respondents' Socio-Demographics

Socio-Demographic Characteristic	Category	Frequency (N)	Percentage (%)
Gender	Male	196	58.0
	Female	142	42.0
	Total	**338**	**100.0**
Age	18-30 years	75	22.2
	31-40 years	143	42.3
	41-50 years	98	29.0
	51 years and above	22	6.5
	Total	**338**	**100.0**
Marital Status	Single	178	52.7
	Married	149	44.1
	Others	11	3.3
	Total	**338**	**100.0**
Educational Qualification	SSCE	18	5.3
	OND/NCE	15	4.4
	HND/B.Sc.	116	34.3
	Master's Degree	137	40.5
	Ph.D.	44	13.0
	Others	8	2.4
	Total	**338**	**100.0**
Years of Experience	Less than 5 years	23	6.8
	6-10 years	140	41.4
	11-15 years	139	41.1
	16 years and above	36	10.7
	Total	**338**	**100.0**
Department	Technology & Data Management	76	22.5
	Human Capital Management	68	20.1
	Strategic & Operational Units	65	19.2
	Risk & Compliance	65	19.2
	Digital & Customer Channels	64	18.9
	Total	**338**	**100.0**
Bank	Access Bank	57	16.9
	First Bank	79	23.4
	GT Bank	70	20.7
	UBA	71	21.0
	Zenith Bank	61	18.0
	Total	**338**	**100.0**

Source: Researchers' field work, 2025

Analysis of Respondents' Socio-Demographics

The sample consists of 58.0% male (196 respondents) and 42.0% female (142 respondents), reflecting broader workforce trends in Nigerian banks. Most respondents (42.3%) are aged 31-40, followed by 29.0% in the 41-50 age range, and 22.2% are between 18-30. The workforce is relatively young to middle-aged, with a mix of experienced professionals and younger employees.

In terms of marital status, 52.7% are single, 44.1% are married, and 3.3% fall into 'Others'. Educationally, most respondents hold a Bachelor's degree or higher, with 40.5% holding a Master's Degree and 13.0% a Ph.D. Industry experience is also considerable, with 41.1% having 11-15 years of work experience, and 41.4% with 6-10 years.

The sample is well-distributed across banking departments, with the highest representation from Technology & Data Management (22.5%), followed by Human Capital Management (20.1%) and Digital & Customer Channels (18.9%). Respondents were drawn from five major Nigerian banks, with First Bank representing the highest proportion (23.4%), followed by UBA (21.0%), GT Bank (20.7%), Zenith Bank (18.0%), and Access Bank (16.9%). This ensures a balanced representation, offering insights into sector-wide trends.

Descriptive Statistics of Research Variables

Table 5 presents descriptive statistics for the key environmental factors affecting Big Data Analytics Adoption (BDAA) in Nigerian banks.

The respondents' responses to the research questions were cumulated in the below table:

Table 5: Respondents' Responses to Research Variables

S/N	Research Variables	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree	Mean	Standard Deviation
1	**Big Data Analytics Adoption (BDAA)**	20	35	62	127	94	3.706	1.1274
2	**Competitive Pressure (CP)**	11	20	58	131	118	3.956	1.0234
3	**External Support (ES)**	21	37	57	129	93	3.698	1.1486
4	**Government Regulations (GR)**	9	22	30	181	96	3.986	0.903
	Average CESF	**15**	**28**	**52**	**142**	**100**	**3.88**	**1.025**

Source: Researchers' Fieldwork, 2025

The descriptive analysis of research variables reveals insights into environmental factors affecting Big Data Analytics Adoption (BDAA) in Nigerian banks.

Regarding BDAA, 65.1% of respondents agreed or strongly agreed that BDA is being adopted in their banks, while 18.3% were undecided, and 16.3% disagreed or strongly disagreed. The mean score of 3.706 with a standard deviation of 1.1274 suggests a generally positive perception of BDA adoption, though some uncertainty remains about its extent.

For Competitive Pressure (CP), 73.7% agreed or strongly agreed that competitive pressure influences BDA adoption, with 17.2% undecided and 9.1% disagreeing. The mean score of 3.956 and a standard deviation of 1.0234 suggest that competitive pressure is widely recognised as a strong motivator for BDA adoption, with low variation in responses.

Regarding External Support (ES), 65.8% of respondents agreed that external support, such as partnerships and consultancy services, plays a role in BDA adoption, while 16.9% were undecided, and 17.1% disagreed. The mean score of 3.698 and a standard deviation of 1.1486 indicate that external support is important but not as strongly perceived as competitive pressure or government regulations.

For Government Regulations (GR), 81.7% of respondents agreed that regulations impact BDA adoption, with 8.9% undecided and 9.2% disagreeing. The mean score of 3.986 and a standard deviation of 0.903 suggest that regulatory policies are seen as a crucial determinant of BDA adoption, with high agreement among respondents.

Overall, 71.6% of respondents recognised the significance of Critical Environmental Success Factors (CESF) in BDA adoption, with a mean score of 3.88 and a standard deviation of 1.025. Competitive pressure and government regulations are the most significant influences, with external support playing a lesser but still relevant role.

Correlation Analysis

Pearson's correlation analysis was conducted to assess the relationship between Big Data Analytics Adoption (BDAA) and the environmental success factors (competitive pressure, external support, and government regulations).

Table 6: Pearson's Correlation Coefficient for All Variables

Variables	BDAA	CP	ES	GR
BDAA	1	0.792**	0.730**	0.680**
Competitive Pressure	0.792**	1	0.669**	0.631**
External Support	0.730**	0.669**	1	0.792**
Government Regulations	0.680**	0.631**	0.792**	1

Note: p < 0.01 (significant at the 1% level).

Analysis of Ordinary Least Square Regression Results

Pearson's correlation analysis examined the relationships between Big Data Analytics Adoption (BDAA) and environmental factors: Competitive Pressure (CP), External Support (ES), and Government Regulations (GR). The results show a strong positive correlation between BDAA and all three factors at the 1% significance level ($p < 0.01$). Competitive Pressure ($r = 0.792$) has the strongest relationship, indicating that as competition intensifies, banks are more likely to adopt BDA to gain a strategic edge. External Support ($r = 0.730$) highlights the role of technology vendors, consultants, and industry alliances in facilitating BDA adoption. Government Regulations ($r = 0.680$) suggest that compliance and regulatory frameworks significantly drive adoption, ensuring better risk management and reporting accuracy. Additionally, environmental factors are significantly correlated with one another. External Support and Government Regulations ($r = 0.792$) indicate that policies may encourage collaborations for BDA adoption. Competitive Pressure and External Support ($r = 0.669$) suggest that banks under high competition seek external assistance for technology adoption. Competitive Pressure and Government Regulations ($r = 0.631$) show that competition and regulations jointly influence technological advancements.

Table 6A: Multicollinearity Diagnostics

Variable	Tolerance	VIF
Competitive Pressure	0.525	1.905
External Support	0.325	3.076
Government Regulations	0.354	2.823

Source: Researchers' computation based on the field survey 2025 using SPSS version 24.

Variance Inflation Factor (VIF) values were examined to assess multicollinearity among the predictor variables. All VIF values were below the threshold of 5.0, indicating that multicollinearity was not a serious concern despite the relatively strong correlations observed among some variables.

Regression Analysis

An Ordinary Least Squares (OLS) regression analysis was conducted to determine the impact of environmental success factors on Big Data Analytics Adoption (BDAA).

Table 7: Regression Analysis Using Ordinary Least Square Estimation Technique

Model	Unstandardized Coefficients		t-Statistics	Probability Value	Hypotheses	Approx. 95% CI
	B	Standard Error				
(Constant)	1.355	.647	2.093	.037	Significant	(0.087, 2.623)
Competitive Pressure	.510	.040	12.813	.000	Significant	(0.432, 0.588)
External Support	.265	.050	5.262	.000	Significant	(0.167, 0.363)
Government Regulations	.138	.052	2.656	.008	Significant	(0.036, 0.240)
R=0.840[a]; R Square=0.706; Adjusted R Square=0.703; Standard Error of the Estimate= 2.19149; F-Stat = 267.025; Durbin-Watson = 1.928						

Source: Researchers' computation based on the field survey 2025 using SPSS version 24.

The R^2 value of 0.706 indicates that 70.6% of the variation in Big Data Analytics Adoption (BDAA) is explained by Competitive Pressure (CP), External Support (ES), and Government Regulations (GR). The adjusted R^2 of 0.703 further confirms the model's strong explanatory power. The F-statistic (267.025, $p < 0.01$) demonstrates that the overall model is statistically significant, implying that the independent variables collectively have a meaningful impact on BDA adoption. The Durbin-Watson statistic (1.928) suggests that there is no severe autocorrelation in the residuals, validating the model's reliability.

Interpretation of Hypotheses

H_{01}: There is no significant relationship between competitive pressure and the adoption of big data analytics in the Nigerian banking sector.

Competitive Pressure ($\beta = 0.510$, $p = 0.000$) has the highest influence on BDA adoption, suggesting that as competition intensifies, banks are more likely to invest in BDA technologies to maintain a competitive edge.

H_{02}: There is no significant relationship between external support and the adoption of big data analytics in the Nigerian banking sector.

External Support ($\beta = 0.265$, $p = 0.000$) is also a significant predictor, indicating that assistance from technology vendors, consultants, and industry collaborations plays a vital role in driving BDA adoption.

H_{03}: There is no significant relationship between government regulations and the adoption of big data analytics in the Nigerian banking sector.

Government Regulations ($\beta = 0.138$, $p = 0.008$), while the least influential among the three factors, remains statistically significant, implying that regulatory frameworks and compliance requirements still play a role in motivating banks to adopt BDA solutions.

Discussion of Findings

The regression results indicate that Critical Environmental Success Factors are significantly associated with Big Data Analytics Adoption (BDAA) among selected quoted deposit money banks in Nigeria. The model explained approximately 70.6% of the variation in BDA adoption ($R^2 = 0.706$), suggesting that Competitive Pressure, External Support, and Government Regulations collectively represent important environmental conditions associated with the adoption of Big Data Analytics within the Nigerian banking sector. The overall model was statistically significant ($F = 267.025$, $p < 0.001$), indicating that the selected environmental factors jointly contribute to explaining variations in BDA adoption.

The first hypothesis examined the relationship between Competitive Pressure and Big Data Analytics Adoption. The findings revealed a significant positive association between Competitive Pressure and BDA adoption ($B = 0.510$, $t = 12.813$, $p < 0.001$). Among the three environmental factors examined, Competitive Pressure emerged as the strongest predictor of BDA adoption. This finding suggests that increasing competition within the Nigerian banking industry encourages banks to

embrace data-driven technologies to enhance operational efficiency, improve customer experience, strengthen risk management capabilities, and maintain competitive positioning.

The growing presence of fintech firms, digital banks, and technology-enabled financial service providers has intensified market competition and increased the need for banks to utilise analytics-driven decision-making. This finding supports Institutional Theory, particularly the concept of mimetic isomorphism, which suggests that organisations tend to imitate successful competitors in order to maintain legitimacy and competitiveness. The finding is consistent with Maroufkhani et al. (2020), who reported that competitive dynamics significantly motivate the adoption of Big Data Analytics. Although Egwuonwu et al. (2023) identified competitive pressure as a relevant environmental factor, they reported an insignificant direct effect on adoption. The difference may be attributed to sectoral variations, as the present study focuses exclusively on the highly competitive and technology-intensive banking industry, whereas Egwuonwu et al. (2023) examined a broader combination of manufacturing and service organisations. Consequently, competitive pressure appears to exert a stronger influence within the banking sector where digital innovation has become a strategic necessity.

The second hypothesis assessed the relationship between External Support and Big Data Analytics Adoption. The results revealed a significant positive association between External Support and BDA adoption ($B = 0.265$, $t = 5.262$, $p < 0.001$). This finding indicates that support from technology vendors, consultants, fintech partners, industry associations, and external service providers is associated with increased levels of BDA adoption among Nigerian banks. The finding supports Resource Dependence Theory, which argues that organisations rely on external actors to acquire critical resources, knowledge, and technological capabilities required for strategic initiatives. Given the technical complexity of Big Data Analytics implementation, external expertise often provides access to specialised skills, technological infrastructure, implementation support, and best practices that facilitate successful adoption. This finding is consistent with Fatima et al. (2024), who reported that environmental support mechanisms positively influence BDA adoption within the financial sector. Similarly, Gupte (2018) emphasised the importance of external expertise and support structures in ensuring successful Big Data projects. The finding therefore suggests that banks that actively engage with external stakeholders may be better positioned to implement analytics technologies effectively.

The third hypothesis examined the relationship between Government Regulations and Big Data Analytics Adoption. The results demonstrated a significant positive association between Government Regulations and BDA adoption ($B = 0.138$, $t = 2.656$, $p = 0.008$). Although Government Regulations emerged as the weakest predictor among the three environmental factors, the relationship remained statistically significant. This finding suggests that regulatory requirements relating to data governance, cybersecurity, risk management, compliance reporting, and customer protection encourage banks to strengthen their analytical capabilities. However, unlike Competitive Pressure, which creates direct market incentives for innovation, regulatory requirements primarily establish compliance obligations within which technology adoption occurs. Consequently, regulations appear to function more as enabling and guiding mechanisms than as primary drivers of adoption. This finding partially supports the work of Bonsu (2024), who reported that regulatory frameworks influence Big Data investments in the banking sector. It also differs from Egwuonwu et al. (2023), who found that regulatory factors exerted insignificant direct effects on adoption. A plausible explanation for this difference is the highly regulated nature of the banking industry, where compliance with Central Bank of Nigeria directives, NDIC regulations, anti-money laundering requirements, cybersecurity frameworks, and data protection regulations creates stronger incentives for adopting advanced analytics systems than may be observed in less regulated sectors.

The findings of this study have important implications for bank executives, information technology managers, policymakers, and regulatory authorities seeking to accelerate Big Data Analytics (BDA) adoption within the Nigerian banking sector. Given that Competitive Pressure emerged as the strongest environmental factor associated with BDA adoption, banks should proactively position themselves to respond to changing market conditions, increasing customer expectations, and competition from fintech firms and digital banking platforms.

First, banks should establish formal partnerships with Big Data Analytics vendors, cloud service providers, fintech organisations, and technology consultants within the next six months. Such partnerships would facilitate access to specialised expertise, advanced analytical tools, implementation support, and emerging technological innovations. Strategic collaborations can also reduce implementation risks and improve the speed and effectiveness of analytics deployment.

Second, banks should conduct quarterly regulatory alignment and compliance audits to ensure that their analytics systems remain consistent with evolving regulatory requirements. Given the increasing emphasis on data governance, cybersecurity, anti-money laundering compliance, and customer data protection, periodic audits can help organisations identify compliance gaps and minimise regulatory risks associated with analytics initiatives.

Third, banks should implement quarterly analytics training programmes for employees across critical functional areas, including Information Technology, Risk Management, Compliance, Operations, Marketing, and Human Capital Management. Continuous training will enhance employees' analytical capabilities, improve data-driven decision-making, and strengthen organisational readiness for advanced analytics adoption. Training programmes should focus on data literacy, analytics interpretation, cybersecurity awareness, and emerging technologies relevant to the banking industry.

Finally, banks should establish executive-level Big Data Analytics Steering Committees responsible for overseeing analytics strategy, implementation, governance, and performance monitoring. The committees should comprise representatives from technology management, risk management, operations, compliance, strategy, and executive leadership functions. Such governance structures will ensure strategic alignment between analytics initiatives and organisational objectives while promoting accountability and effective resource allocation.

5. CONCLUSION AND REVOMMENDATIONS

This study examined the critical environmental success factors influencing Big Data Analytics (BDA) adoption in Nigerian banks, focusing on competitive pressure, external support, and government regulation. The findings indicate that environmental factors significantly affect BDA adoption decisions. Competitive pressure from peers and external support from technology vendors and consultants play key roles in motivating banks to adopt BDA. Additionally, government regulations provide a framework within which BDA adoption can be successfully implemented, ensuring compliance and fostering trust in the technology. In conclusion, environmental factors create a conducive environment for BDA adoption, but banks must strategically manage external pressures and leverage available support systems to optimise the benefits of BDA.

Based on the findings of this study, the following recommendations are provided:

i. Nigerian banks should use competitive pressure as a motivation to adopt BDA, ensuring they remain at the forefront of digital transformation, technological advancements and maintain a competitive edge.

ii. Banks should establish partnerships with external stakeholders such as technology vendors, consultants, and industry bodies to gain the necessary expertise, access cutting-edge tools and resources for the successful implementation of BDA adoption.

iii. Nigerian banks must ensure that their BDA initiatives align and comply with existing government regulations and take advantage of any regulatory support or incentives provided by the government to encourage technology adoption.

Despite its contributions, this study has several limitations that should be considered when interpreting the findings. First, the study adopted a cross-sectional survey design in which data were collected at a single point in time. Consequently, the findings demonstrate associations between environmental success factors and Big Data Analytics adoption but do not establish causal relationships. Changes in environmental conditions and organisational responses over time were not captured by the study design.

Second, the study relied primarily on self-reported data obtained from employees of selected deposit money banks. As with most survey-based research, the possibility of common method bias and respondent subjectivity cannot be entirely eliminated despite efforts to ensure data quality and confidentiality.

Third, the regression model did not include control variables such as bank size, organisational age, digital maturity, employee experience, educational background, or ownership structure. These factors may influence Big Data Analytics adoption and could potentially affect the magnitude of the relationships observed in this study. Consequently, the findings should be interpreted within the context of the selected environmental variables examined.

Finally, the study focused exclusively on quoted deposit money banks in Nigeria. Therefore, caution should be exercised when generalising the findings to non-banking sectors or financial institutions operating under different regulatory and competitive environments.

Future studies should address the limitations of the present investigation by employing longitudinal research designs that examine Big Data Analytics adoption over multiple periods. Longitudinal studies would provide deeper insights into how environmental factors shape analytics adoption over time and would strengthen understanding of potential causal relationships.

Future researchers should also incorporate relevant control variables such as organisational size, digital capability, ownership structure, organisational age, and employee experience to isolate the unique effects of environmental success factors on Big Data Analytics adoption.

In addition, comparative studies involving multiple sectors, including banking, insurance, telecommunications, manufacturing, and healthcare, would improve understanding of sector-specific drivers of analytics adoption. Cross-country investigations across emerging economies would further reveal how regulatory environments, technological infrastructure, and institutional conditions influence adoption decisions.

Finally, future studies may employ mixed-method approaches that combine quantitative surveys with qualitative interviews and case studies to provide richer insights into the organisational processes, challenges, and strategic considerations associated with Big Data Analytics adoption.

REFERENCES

Ajimoko, O. J. (2018). Considerations for the adoption of cloud-based big data analytics in small business enterprises. *The Electronic Journal of Information Systems Evaluation, 21*(2), 63-79. Available at www.ejise.com.

Al-Dmour, H., Saad, N., Basheer Amin, E., Al-Dmour, R., & Al-Dmour, A. (2020). The influence of the practices of big data analytics applications on bank performance: Field study. *VINE Journal of Information and Knowledge Management Systems, 53*(1), 119–141. https://doi.org/10.1108/VJIKMS-08-2020-0151

Aziz, N. A., Long, F., & Wan Hussain, W. M. (2023). Examining the effects of big data analytics capabilities on firm performance in the Malaysian banking sector. *International Journal of Financial Studies, 11*(1), 23. https://doi.org/10.3390/ijfs11010023

Baig, M. I., Shuib, L., & Yadegaridehkordi, E. (2019). Big data adoption: State of the art and research challenges. *Information Processing & Management, 56*, 102095. https://doi.org/10.1016/j.ipm.2019.102095

Belhadi, A., Zkik, K., Cherrafi, A., & Sha'ri, M. Y. (2019). Understanding big data analytics for manufacturing processes: Insights from literature review and multiple case studies. *Computers & Industrial Engineering, 137*, 106099.

Bonsu, M. O. A. (2024). *Big data, Financial Innovation and Financial Performance. Evidence from the UK Banking Sector* (Doctoral dissertation, Teesside University).

Brock, V., & Khan, H. U. (2017). Big data analytics: Does organisational factor matter in technology acceptance? *Journal of Big Data, 4*, 21. https://doi.org/10.1186/s40537-017-0081-8

Bullen, C., & Rockart, J. (1981). A primer on critical success factors. *Center for Information Systems Research, Sloan School of Management.*

Camarinha-Matos, L. M., Fornasiero, R., Ramezani, J., & Ferrada, F. (2019). Collaborative networks: A pillar of digital transformation. *Applied*

Sciences, 9(24), 5431. https://doi.org/10.3390/app9245431

Coleman, S., Goeb, R., Manco, G., Pievatolo, A., Tort-Martorell, X., & Reis, M. S. (2016). How can SMEs benefit from big data? Challenges and a path forward. *Quality and Reliability Engineering International, 32*(6), 2151–2164. https://doi.org/10.1002/qre.1984

Diniz, E. H., Luvizan, S. S., Hino, M. C., & Ferreira, P. C. (2018). Unveiling the big data adoption in banks: Strategizing the implementation of a new technology. In *Digital Technology and Organisational Change* (pp. 149–162). Springer.

Du, S., Yalcinkaya, G., & Bstieler, L. (2016). Sustainability, social media-driven open innovation, and new product development performance. *Journal of Product Innovation Management, 33*(S1), 55–71. https://doi.org/10.1111/jpim.12334

Egwuonwu, A., Mendy, J., Smart-Oruh, E., & Egwuonwu, A. (2023). Drivers of Big Data analytics' adoption and implications of management decision-making on Big Data adoption and firms' financial and nonfinancial performance: Evidence from Nigeria's manufacturing and service industries. *IEEE Transactions on Engineering Management, 71*, 11907-11922.

Fatima, M., Malik, B., Ayub, H., & Ellahi, A. (2024). Adoption of big data analytics and banks' performance: The moderating role of analytics capability. *Migration Letters, 21*(S13), 164-184. https://www.migrationletters.com

Ferraris, A., Mazzoleni, A., DeValle, A., & Couturier, J. (2019). Big data analytics capabilities and knowledge management: Impact on firm performance. *Management Decision, 57(8)*, 1923–1936. https://doi.org/10.1108/MD-02-2018-0254

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How "big data" can make a big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics, 165*, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031

Frisk, J. E., & Bannister, F. (2017). Improving the use of analytics and big data by changing the decision-making culture. *Management Decision, 55(10)*, 2074–2088. https://doi.org/10.1108/MD-04-2016-0224

Gangwar, H. (2018). Understanding the determinants of big data adoption in India. *Information Resources Management Journal, 31*(4), 1–22. https://doi.org/10.4018/irmj.2018100101

Gatali, I. F., Lee, K. Y., Park, S. U., & Kang, J. (2016). A qualitative study on adoption of biometrics technologies: Canadian banking industry. *Proceedings of the 18th Annual International Conference on Electronic Commerce: e-Commerce in Smart Connected World*, 1-8.

Ghasemaghaei, M. (2018). Improving organisational performance through the use of big data. *Journal of Computer Information Systems, 60(5)*, 395–408. https://doi.org/10.1080/08874417.2018.1432991

Grimaldi, D. (2020). Factors affecting big data analytics-based innovation processes: A Spanish evidence. *International Journal of Innovation and Technology Management, 17(1)*. https://doi.org/10.1142/S0219877020500054

Grimaldi, D., Diaz, J., Arboleda, H., & Fernandez, V. (2019). Data maturity analysis and business performance: A Colombian case study. *Heliyon, 5(9)*, e02195. https://doi.org/10.1016/j.heliyon.2019.e02195

Gupte, A. (2018). *Determining critical success factors for big data projects* (Master's thesis, Purdue University).

Hasan, M. M., Popp, J., & Oláh, J. (2020). Current landscape and influence of big data on finance. *Journal of Big Data, 7*(1). https://doi.org/10.1186/s40537-020-00291-z

Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA)

adoption in logistics and supply chain management. *The International Journal of Logistics Management, 29*(2), 676–703. https://doi.org/10.1108/ijlm-06-2017-0153

Lateef, M., & Keikhosrokiani, P. (2023). Predicting Critical success factors of business intelligence implementation for improving SMEs' performances: a case study of Lagos State, Nigeria. *Journal of the Knowledge Economy*, *14*(3), 2081-2106.

Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2023). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems*, *123*(1), 278-301.

Maroufkhani, P., Tseng, M., Iranmanesh, M., Ismail, W. K., & Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management, 54*, 102190. https://doi.org/10.1016/j.ijinfomgt.2020.102190

Maroufkhani, P., Wagner, R., Wan Ismail, W. K., Baroto, M. B., & Nourani, M. (2019). Big data analytics and firm performance: A systematic review. *Information, 10*(7), 226.

Maroufkhani, P., Wan Ismail, W. K., & Ghobakhloo, M. (2020). Big data analytics adoption model for small and medium enterprises. *Journal of Business Research*, 112, 335-343. https://doi.org/10.1016/j.jbusres.2020.01.020

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research, 98*, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044

Nasrollahi, M., & Ramezani, J. (2020). A model to evaluate the organisational readiness for big data adoption. *International Journal of Computers Communications & Control, 15(1)*. https://doi.org/10.15837/ijccc.2020.1.3884

Nobanee, H., Dilshad, M. N., Al Dhanhani, M., Al Neyadi, M., Al Qubaisi, S., & Al Shamsi, S. (2021). Big data applications in the banking sector: A bibliometric analysis approach. *SAGE Open, 11*(4). https://doi.org/10.1177/21582440211067234

Owusu, A., Broni, F. E., Penu, O. K. A., & Boateng, R. (2020). Exploring the critical success factors for cloud BI adoption among Ghanaian SMEs. *AMCIS 2020 Proceedings*, 21. Retrieved from https://aisel.aisnet.org/amcis2020/adoption_diffusion_IT/adoption_diffusion_IT/21

Park, J. H., & Kim, Y. B. (2021). Factors activating big data adoption by Korean firms. *Journal of Computer Information Systems, 61*(3), 285–293. https://doi.org/10.1080/08874417.2019.1631133

Phan, D. T., & Tran, L. Q. T. (2022). Building a conceptual framework for using big data analytics in the banking sector. *Intellectual Economics, 16*(1), 5–23. https://doi.org/10.13165/IE-22-16-1-01

PwC. (2013). Where have you been all my life? How the financial services industry can unlock the value in big data. *PwC FS Viewpoint, October 2013*.

Raguseo, E., & Vitari, C. (2018). Investments in big data analytics and firm performance: An empirical investigation of direct and mediating effects. *International Journal of Production Research*, *56*(15), 5206-5221.

Ramezani, J., & Camarinha-Matos, L. M. (2019). A collaborative approach to resilient and antifragile business ecosystems. *Procedia Computer Science, 162*, 604–613. https://doi.org/10.1016/j.procs.2019.11.016

Rogers, E. M. (1993). The diffusion of innovations model. *Diffusion and Use of Geographic Information Technologies*, 9–24. https://doi.org/10.1007/978-94-011-1771-5_2

Seseni, L., & Mbohwa, C. (2021). The significance of big data in the success of SMEs in emerging markets: A case of South Africa.

In *Proceedings of the 11th annual International Conference on Industrial Engineering and Operations Management* (pp. 1986-1996).

Singh, J., Singh, G., Gahlawat, M., & Prabha, C. (2022). Big data as a service and application for the Indian banking sector. *Procedia Computer Science, 215*, 878-887. https://doi.org/10.1016/j.procs.2022.02.118

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of big data challenges and analytical methods. *Journal of Business Research, 70*, 263-286. https://doi.org/10.1016/j.jbusres.2016.08.012

Soubra, L. (2021). Big data, customer centricity, and sustainability in the banking industry. *BAU Journal-Creative Sustainable Development, 3*(1), 11-19. https://doi.org/10.38061/1956-2118

Tiwari, S., Wee, H.-M., & Daryanto, Y. (2018). Big data analytics in supply chain management between 2010 and 2016: Insights to industries. *Computers & Industrial Engineering, 115*, 319–330. https://doi.org/10.1016/j.cie.2017.11.017

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Free Press.

Truong, N. X. (2022). Factors affecting big data adoption: An empirical study in small and medium enterprises in Vietnam. *International Journal of Asian Business and Information Management, 13*(1), 1–21. https://doi.org/10.4018/IJABIM.315825

Turner, D., Schroeck, M., & Shockley, R. (2013). Analytics: The real-world use of big data in financial services. *IBM Global Business Services, 27*(1), 16.

Vassakis, K., Petrakis, E., & Kopanakis, I. X. (2017). Big data analytics: Applications, prospects, and challenges. In *Mobile big data: A roadmap from models to technologies* (pp. 1–22). Springer. https://doi.org/10.1007/978-3-319-67925-9_1

Verma, S., & Bhattacharyya, S. S. (2017). Perceived strategic value-based adoption of big data analytics in emerging economies. *Journal of Enterprise Information Management, 30*(3), 354–382. https://doi.org/10.1108/JEIM-10-2015-0099

Wamba, S. F. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organisational agility and customer agility. *International Journal of Information Management, 67*, 102544. https://doi.org/10.1016/j.ijinfomgt.2022.102544

Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics, 165*, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009