**The Role of Business Analytics on Operational Efficiency of Organisations in Nigeria**

**Abstract**

The uniqueness of Nigeria’s business environment has not allowed firms to holistically incorporate all these components in achieving financial and operational performance. Knowing fully well that Nigeria has a wide and multidimensional business spread. This study examines into the effect of business analytics on operational efficiency of organization in Nigeria. The study employed the descriptive survey design in selecting one hundred respondent from five different industry in Nigeria. The regression analysis and descriptive analysis was used for drawing inferences for the findings. The findings reveals that data management has positive significant effect on operational efficiency. Data visualization has positive insignificant effect on operational efficiency. Technology tools and usage has positive insignificant effect on operational efficiency. The results highlight the critical role of data management as the backbone of operational success. While technology tools and data visualization techniques are important enablers, they must be effectively aligned with robust data management practices to realize their potential.

**Keyword:** Business analytics; Data management; Data visualization and Operational efficiency

**1.1 Introduction**

Business analytics is becoming the new normal in determining the operational efficiency and effectiveness of firms, both locally and internationally (Oberg & Graham, 2016; Tsiu et al., 2024). Business analytics can be described as systems, tools, practices, and applications that help businesses analyze operational and organizational events, enabling them to better understand their enterprise and make accurate and informed decisions (Ramanathan et al., 2017; Conboy et al., 2020).

Business analytics refers to the capabilities used to collect, store, analyze, and derive insights from accumulated data to support the decision-making processes within an organization (Komolafe et al., 2024; Riipa et al., 2025). These are systems that offer value creation and competitive advantages to organizations. They assist in improving business patterns, enhancing firm performance, and establishing a competitive edge (Komolafe et al., 2024; Riipa et al., 2025). Business analytics enables organizations to build descriptive, predictive, and prescriptive models using real-time, diverse, and large-scale data sources (Duan et al., 2019; Hindle & Vidgen, 2018).

Furthermore, business analytics comprises several core components, including data management, descriptive analytics, diagnostic analytics, predictive analytics, prescriptive analytics, data visualization, and technological tools and software (Johnson, et al., 2019; Grover, et al., 2020). The uniqueness of Nigeria’s business environment has not allowed firms to holistically incorporate all these components in achieving financial and operational performance (Adewusi et al., 2024; Kraus et al., 2020). Data management involves the collection, cleaning, storage, and integration of raw data into meaningful insights that inform decision-making, while data visualization entails the use of tools such as Power BI, Tableau, and Excel dashboards to communicate insights to decision-makers and other internal/external stakeholders (Power et al., 2018; Komolafe et al., 2024).

Studies such as Rahman et al. (2023), Conboy et al. (2023), Michael et al. (2019), Ramanathan et al. (2017), and Sharma et al. (2014) have not adequately examined how the peculiarities of these core components of business analytics affect the operational performance of firms in the Nigerian context, particularly using a qualitative research approach. Operational performance reflects how effectively and efficiently an organization carries out its core business activities, including how it manages labor, equipment, and materials (through business analytics) to ensure accurate delivery of products and services to internal and external stakeholders. Based on the above premise, this study investigates the role of business analytics in the operational efficiency of selected organizations in Nigeria.

**2.1 Literature Review**

**2.1.1 Business Analytics**

Business analytics is broadly understood as a combination of tools, technologies, methods, and applications that help organizations examine critical business data. Seddon and Currie (2017) define it more specifically as the use of data to support evidence-based problem identification and decision-making within business settings a definition adopted in this study. However, existing definitions and classifications of business analytics are limited and often inconsistent across studies (Mikalef et al., 2018; Seddon & Currie, 2017). To provide a clearer and more actionable definition, this study refers to the work of Mikalef et al. (2018), who systematically reviewed the literature and identified key characteristics of business analytics data. These core features include the **volume, velocity,** and **variety** of data (Sun, Chen & Yu, 2015). Some researchers have expanded this view to include additional attributes such as **veracity** (Abbasi et al., 2016; Akter et al., 2016), **variability** (Hazen et al., 2018; Seddon et al., 2012), and **visualization** (Seddon & Currie, 2017).

**2.1.2 Business Analytics and Operational Performance**

Business analytics commonly refers to the processes of collecting, storing, analyzing, and interpreting data to support better decision-making and enhance organizational performance (Aydiner et al., 2019; Kraus et al., 2020). It is also seen as the transformation of raw data into actionable insights about an organization’s capabilities, market position, operations, and strategic opportunities key to maintaining competitiveness. These definitions highlight two central components of value creation in business analytics: technology and human intervention.

The core functionalities of business analytics technologies include tools such as online analytical processing (OLAP), querying, reporting, data mining, visualization, and various statistical and quantitative techniques. These tools rely on integrated databases and data warehouses that enable efficient data retrieval and analysis (Riipa et al., 2025). Recent advancements in integrating previously isolated information systems (IS) have significantly broadened the scope of business analytics, enabling real-time and intelligent insights that support managerial decision-making and strategic investments. Building on Sharma et al. (2010), it is argued that firms realize performance improvements from business analytics primarily through the reconfiguration of internal resources and routines. This process depends heavily on organizational capabilities and managerial insight. This perspective aligns with earlier research findings (Aydiner et al., 2019; Kraus et al., 2020), although much of the literature has relied on case studies. Therefore, there is a need for a theoretically grounded framework to better explain how business analytics contributes to improved operational performance.

**2.2 Theoretical Framework**

**2.2.1 Resource-Based Theory**

The resource-based theory of the firm, introduced by Wernerfelt (1984), is a widely referenced theory in strategic management due to its practical relevance to contemporary practices. This theory emphasizes that organizational capabilities significantly influence performance (Priem and Butler, 2001). The resource-based view (RBV) posits that a firm's competitive advantage and superior performance stem from the characteristics of its resources and capabilities, which must be valuable and difficult to replicate.

Building on the assumptions that strategic resources are unevenly distributed across firms and remain stable over time, the RBV asserts that a firm’s resources and capabilities define its strategy and performance. If all firms in a market possess identical resources and capabilities, they would generate equal value, eliminating any competitive advantage (Barney, 1991). The core idea of the RBV is that successful firms achieve future competitiveness by developing distinctive and unique capabilities, often intangible or implicit. Therefore, a firm's strategy should revolve around leveraging its unique resources and capabilities. Additionally, a firm's ability to establish and sustain a profitable market position depends on the value-creating potential and rent-generating capacity of its resources and capabilities (Kimani, 2016; Madhani, 2010).

The Resource-Based View (RBV) theory suggests that a firm’s performance is driven by its resources, which can be tangible (like physical assets) or intangible (such as knowledge, skills, and organizational processes) (Barney, 1991; Wade & Hulland, 2004). For resources to provide a strategic advantage, they must be valuable, rare, inimitable, and non-substitutable (Barney, 1991). Organizational capabilities defined as the firm’s ability to effectively use technology, processes, and human expertise play a vital role in turning these resources into a competitive edge.

According to RBV, unique capabilities help firms operate more efficiently and effectively than rivals, leading to superior performance (Amit & Schoemaker, 1993). This framework has been widely used to highlight the strategic value of information technology (IT) assets (Melville et al., 2004; Ray et al., 2005; Mishra et al., 2007). For instance, businesses investing in analytics-driven customer relationship management (CRM) systems have enhanced their customer-related capabilities, thereby improving firm performance (Coltman, 2007; Coltman et al., 2011). In line with RBV, this study acknowledges the strategic importance of business analytics in today’s data-driven environment. It emphasizes how analytics-driven insights are integrated into business processes and decision-making routines to create value and sustain competitive advantage.

**2.3 Empirical Review**

Rahman (2023) investigated into the effect of business intelligence on bank operational efficiency and Perceptions of profitability of selected deposit money banks. The subject matter was to business intelligence would spur operational efficiency and how it would also spur bank profitability. The study was anchored on resource based theory. The study employed the simple random sampling technique is sourcing for information from two hundred and seventy respondent spread across thirty eight banks. The study used the partial-least square and structural equation modelling to determine the direct and indirect relationship between the construct in the research title. The findings reveals that business intelligence is positively associated with operational efficiency and profitability and also that operational efficiency through business intelligence has a positive effect on bank’s profitability.

Conboy et al., (2020) examines into the deployment of business analytics to spur and improve dynamic capabilities in operations. The subject matter was to examine how business analytics could increase the dynamic capabilities (sensing, seizing, transforming) and effectively improve firm analytic attributes (volume, velocity, variety, variability, veracity and visualization). This study draws on the dynamic capabilities view of the firm and builds on eight selected case studies of operations research activity in large organisations, each of which have invested significantly in analytics technology and implementation. The study identifies fourteen analytics-enabled micro-foundations of dynamic capabilities, essentially high- lighting how organisations can use analytics to manage and enhance their OR activities in dynamic and uncertain environments.

Michael O’Neill & Anthony Brabazon (2019) examines into the inter-relationship between business analytics capability, organizational value and competitive advantage. The subject matter was determined if there is any relationship between business analytics capability levels with value and competitive advantage generation. The study employed the descriptive survey design, where sixty-four senior analytics professionals from seventeen sectors where selected. The study employed the Pearson’s product moment correlation that shows that there is positive correlation between business capabilities and organizational value and advantage.

Ramanathan, et al., (2017) examines into how the adoption of business analytics would enhance performance. The subject matter was to test the impact of business analytics capturing the technology, organization and environment framework in determining performance in retail firms. The study has been able to verify through empirical works the tenets of technology, organization and environment framework in the adoption of business analytics in retail companies in U.K.

Asadi Someh & Shanks (2015) examines into how business analytics systems provide benefits and contribute to firm performance. The subject matter is to determine how business analytics capability, analytical CRM and capability improves firm performance and also when informational benefits in captured has a moderating variable. The study is anchored on the resource based theory, theming on IT capabilities, IT asset classes and Process-oriented perspective improves business value of Information technology. The findings reveals that business analytics capability has some direct effect on informational benefits, this effect indicates that the implementation of business analytics helps organizations change their routines and behaviors and culture.

Sharma, et al., (2014) examines into the impact of business analytics on organization taking cognizance of the transforming decision making process. The subject matter was to determine how business analytics influence organizational decision-making processes, the joint effects of the use of business analytics in quantifying organizational performance. The study is a theoretical and conceptual study. The also captures how does organizational structures, routines and decision making process influence the ability of managers, how does human sense and machine learning work together to improve the generation of insights from the use of business analytics; how do the structures and process of accurate decision making influence the ability of insight generation teams to generate insights from the use of business analytics. The study concluded that business analytics could help decision making which in the long run spur operational efficiency.

Anand, et al., (2013) investigated into the routines, reconfiguration and the contribution of business analytics to enhance organizational performance. The subject matter is to theoretical identify organizational factors that would spur performance and competitive advantage from the integration of business analytics. The study was able to illustrate how business analytics spur routines and agency, dynamic capabilities, Information and technology system. The study concluded that business analytics serves as a potential tool for the firms in strategy creation and distinguishing themselves from its competitors.

Graeme Shanks & Nargiza Bekmamedova (2012) investigated into achieving business benefits with business analytics systems. The subject matter was to evaluate how business analytics spur organizational and dynamic capabilities and towards achieving value of competitive advantage in financial institutions. The study employed the case study approach by juxtaposing the organizational structure and attributes with the dynamic capabilities of business analytics in such organization. The study concluded that embedding business analytics systems within the organization occurs in five different levels which includes a high quality technology and data infrastructure, aligned with the organization business processes, decision making routine, and evidence based management.

Shanks, et al., (2012) investigated into the how business analytics enables strategic alignment and organizational transformation. The study was able to discuss three areas like business analytics, strategic alignment, IT strategy and enterprise architecture operating models. The study employed the case study approach which allowed data of warehousing and global reporting group within international mining company. The respondent were the senior managers, Business analytics technical experts and Business analytics business experts. The study was able to illustrate factors that are critical to strategic alignment and organisational transformation which includes; early definition of standardized metrics and dimensions, high quality technology and data infrastructure, senior management support, change management and governance and people with hybrid skills. The conclusion of this inquiry is that local and global organization towards their implementation of business analytics within the business strategy would become more unified using common core business processes.

Trkman, et al., (2010) examines into the impact of business analytics on supply chain performance. This study investigated into the relationship between business analytics capabilities in terms of plans, source make and delivery areas of supply chain and performance aided with business processes and information system support. The quantitative research employed sourced for data from three hundred and ten companies in USA, Europe, Canada, Brazil and China. Structural equation modelling reveals that there is statistical significant relationship between analytical capabilities and performance, inclusively that when moderating effect of information system supports is factored it releases a stronger effect on business process orientation.

**3.1 Methodology**

The employed the qualitative research approach, that informed the usage of descriptive survey design. The study employed one hundred sample size from various industries that are averse and adjusting to the peculiarity of business analytics (service industry, banking industry, manufacturing industry and Agricultural industry) in Lagos State. The independent variables in the research process includes; data management; data visualization and technology and tools usage while the dependent variable is the operational efficiency. The study employed the usage of questionnaire to source for data/information from the respondent.

**3.1.1 Model Specification**

This model was adapted and adjusted to suit the present study from the works of Rahman (2023) and Conboy et al., (2020).

The linear equation is given below;

$OPE\_{i}=f\left(BUA\_{t}\right)$…………………………………………………………….1

$BUA\_{t}=f\left(DM\_{t,}DV\_{t,}TTU\_{t,}\right)$………………………………2

Where:

OPE; Operational Efficiency at time t

BUA; Business analytics at time t

**Independent Variable**

DM: Data management at time t

DV: Data Visualization at time t

TTU: Technology and Tools Usage at time t

**4.1 Results and Discussion**

**Table 1: Descriptive Analysis**

|  |
| --- |
| **Descriptive Statistics** |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Skewness | Kurtosis |
| Statistic | Statistic | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| Operational\_Efficiency | 100 | 7.00 | 16.00 | 10.6600 | 2.94468 | .344 | .241 | 1.174 | .478 |
| Data\_Management | 100 | 7.00 | 17.00 | 11.2500 | 3.49711 | .312 | .241 | 1.277 | .478 |
| Data\_Visualization | 100 | 9.00 | 18.00 | 13.6800 | 2.53413 | .148 | .241 | 1.025 | .478 |
| Technology\_Tools\_Usage | 100 | 6.00 | 17.00 | 11.5500 | 3.39451 | .085 | .241 | 1.070 | .478 |
| Valid N (listwise) | 0 |  |  |  |  |  |  |  |  |

**Researcher’s Field Survey, 2025**

Table 1 showed operational efficiency has a mean value (average value) of 10.6. The highest value of 16.00 and lowest value 7.00. The standard deviation shows that level of disparity of the group from the mean value of 10.6 is 2.94. The skewness is positively skewed at 0.34 and the kurtosis is leptokurtic at 1.17 (less than 3). Data management has a mean value (average value) of 11.2. The highest value of 17.00 and lowest value of 7.00. The standard deviation shows that level of disparity of the group from the mean value of 11.1 is 3.49. The skewness is positively skewed at 0.31 and the kurtosis is leptokurtic at 1.27 (less than 3). Data visualization has a mean value (average value) of 13.6. The highest value of 18.00 and lowest value of 9.00. The standard deviation shows that level of disparity of the group from the mean value of 13.6 is 2.53. The skewness is positively skewed at 0.14 and the kurtosis is leptokurtic at 1.02 (less than 3). Technology\_Tools usage has a mean value (average value) of 11.55. The highest value of 17.00 and lowest value of 6.00. The standard deviation shows that level of disparity of the group from the mean value of 11.55 is 3.39. The skewness is positively skewed at 0.08 and the kurtosis is leptokurtic at 1.07 (less than 3).

**Table 2: Correlation Matrix**

|  |
| --- |
| **Correlations** |
|  | Operational\_Efficiency | Data\_Management | Data\_Visualization | Technology\_Tools\_Usage |
| Operational\_Efficiency | Pearson Correlation | 1 | .916\*\* | .477\*\* | .898\*\* |
| Sig. (2-tailed) |  | .000 | .000 | .000 |
| N | 100 | 100 | 100 | 100 |
| Data\_Management | Pearson Correlation | .916\*\* | 1 | .482\*\* | .977\*\* |
| Sig. (2-tailed) | .000 |  | .000 | .000 |
| N | 100 | 100 | 100 | 100 |
| Data\_Visualization | Pearson Correlation | .477\*\* | .482\*\* | 1 | .409\*\* |
| Sig. (2-tailed) | .000 | .000 |  | .000 |
| N | 100 | 100 | 100 | 100 |
| Technology\_Tools\_Usage | Pearson Correlation | .898\*\* | .977\*\* | .409\*\* | 1 |
| Sig. (2-tailed) | .000 | .000 | .000 |  |
| N | 100 | 100 | 100 | 100 |
| \*\*. Correlation is significant at the 0.01 level (2-tailed). |

**Researcher’s Field Survey, 2025**

Table 2 showed that operational efficiency has a positive relationship with data management at (p: 0.916; p<0.05); Data visualization at (p: 0.477; p<0.05); Technology\_tools and usage at (p: 0.898; p<0.05).

**Table 3: Multiple Regression Analysis**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variable** | **Co-efficient** | **Std-Error** | **t-stat** | **P-value** |
| **Constant** | 1.208 | 0.745 | 1.622 | 0.108 |
| **Data Management** | 0.736 | 0.178 | 3.494 | 0.001 |
| **Data Visualization** | 0.058 | 0.057 | 3.494 | 0.239 |
| **Technology/Tools usage** | 0.155 | 0.176 | 0.764 | 0.447 |
|  |  |  |  |  |
| **R2** | 0.841 | **F.cal** | 169.262 |
| **Adj. R2** | 0.836 | **Sig.F** | 0.000 |

**Researcher’s Field Survey, 2025**

Table 3 depicted that data management has positive significant effect on operational efficiency at *(β1= 0.736; ρ<0.05).* Data visualization has positive insignificant effect on operational efficiency at *(β1= 0.058; ρ<0.05).* Technology\_tools and usage has positive insignificant effect on operational efficiency at *(β1= 0.155; ρ<0.05).* The tables of revealed that {F-cal= 169.262, *ρ*< 0.05}, which showed that the overall model is statistically significant at 5% level of significance.

R2 is a measure of goodness of fit of the regression model. It revealed that, the independent variable data management, data visualization and technology and tools usage account for 0.841 (84.1%) variation or change in the dependent variable operational efficiency and if any additional variable is added it will still explain the variable at 0.836 (83.6%). The findings implies that data management plays a crucial role in improving efficiency, this informs that organization that invest in effective data collection, storage and organization processes are more likely to experience enhanced operational performance. In contrast to the construct of data visualization and technology tools and usage, this indicates that simple adopting visualization technique or technology tools without integrating them into a broader strategic data management framework may not significantly impact operational outcomes. Therefore while technology and visualization tools are valuable, their true benefits are likely realized only when anchored on strong data management practices. Organization should prioritize building robust data management systems before substantial gains from technology adoption or visualization initiatives.

**5.1 Conclusion and Recommendation**

This suggests that organizations that prioritize structured data collection, secure storage, effective retrieval, and strategic use of data are more likely to achieve improvements in their operational processes. High-quality data management practices provide a reliable foundation for informed decision-making, process optimization, and resource management, thereby enhancing overall efficiency. Although data visualization and technology/tools usage are generally considered supportive to operational improvements, their insignificance in this study suggests that their mere presence or use without a strong underlying data management system may not yield substantial operational benefits. The results highlight the critical role of data management as the backbone of operational success. While technology tools and data visualization techniques are important enablers, they must be effectively aligned with robust data management practices to realize their potential. Thus, organizations seeking operational efficiency gains should prioritize building and maintaining strong data management capabilities, using visualization and technology tools as complementary, rather than primary, strategies. Nigerian business should commence and continually integrate business intelligence in all levels of their operations to ensure increase in the level of productivity

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