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Leveraging Business Intelligence for Strategic Decision Making: Analyzing Its Impact on MTN Nigeria's Organizational Performance

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Abstract

Business Intelligence (BI) has emerged as a critical tool for enhancing organizational decision-making in dynamic industries like telecommunications. In Nigeria's telecommunication sector, data-driven insights are vital for maintaining a competitive edge where BI systems play a crucial role. This study investigates the impact of BI on organizational decision-making within MTN Nigeria where a mixed-method approach was used, combining descriptive and *ex-post facto* designs with a survey methodology. A structured questionnaire was administered to 316 respondents from a population of 1495, determined through stratified and random sampling using Yamane's formula. Data was analyzed using descriptive statistics and Structural Equation Modeling (SEM) to evaluate the relationships between various BI components and decision-making processes. The findings show that while BI has a significant overall impact on decision-making, the influence of specific BI components varies. Business Intelligence cost, data quality, data security, and technical expertise were found to significantly impact service, processing, and risk decisions. Conversely, data integration and data security did not have significant effects on service and processing decisions, and data integration and data quality showed no significant impact on risk decisions. These findings highlight the need for MTN Nigeria to strategically align its BI investments with the specific needs of different decision-making areas. The study recommends investing in cost-effective BI solutions, enhancing data security, improving data quality, and fostering technical expertise to optimize decision-making and operational performance in the telecommunication industry.

Keywords

Business Intelligence, Business Analytics, Strategic Decision

1. Introduction

Business Intelligence (BI) has become an essential component for organizations seeking to enhance their decision-making processes by leveraging data-driven insights (Dedic & Stanier, 2016; Kimball & Ross, 2016). BI encompasses a wide range of activities, applications, and technologies that facilitate the collection, analysis, and visualization of business data, ultimately supporting both operational and strategic decision-making (IBM, 2011). As organizations increasingly recognize the potential of BI to provide a competitive advantage, they are paying close attention to critical factors such as data quality, data integration, data security, BI costs, and technical expertise (Kappelman, McLean, Luftman, & Johnson, 2013). In the fast-paced and highly competitive telecommunications industry, Business Intelligence has emerged as a vital tool for gaining insights into customer behavior, improving operational efficiency, and responding to market dynamics (Negro & Mesia, 2020). Organizations like MTN Nigeria, a leading telecommunications company, are leveraging BI to make smarter decisions that can enhance their performance and maintain their market leadership (Chugh & Grandhi, 2013). With the rapid expansion of digital transformation technologies such as big data analytics and artificial intelligence, BI has evolved from a niche concept into a mainstream practice, enabling organizations to respond effectively to globalization, deregulation, competition, and technological advancements (Caserio & Trucco, 2018; Osiobe & Winingham, 2020).

Effective Business Intelligence is contingent upon the quality and accuracy of the data being used. High-quality data enables organizations to better understand their customers, monitor network performance, and make more informed decisions, particularly in the telecommunications industry, where data is vast and often unstructured (Rumisha et al., 2020; Osiobe, 2019a). Data integration is another critical factor in the success of BI initiatives, especially as organizations like MTN Nigeria must merge disparate data sources such as customer interactions, network infrastructure, and sales data into a unified platform for analysis (Negro & Mesia, 2020; Osiobe, 2020b). Data security is of paramount importance in the telecommunications sector, where breaches or unauthorized access to sensitive customer data can have devastating consequences for both organizational reputation and financial standing (O'Loughlin, Neary, Adkins, & Schueller, 2019; Osiobe, 2023). Consequently, companies like MTN Nigeria must invest in robust data security measures to ensure that their BI systems are well-protected against cyberattacks (Osiobe et al., 2024a).

However, implementing and maintaining a comprehensive BI system also comes with significant costs, including software licensing, infrastructure, training, and ongoing maintenance (Wahua & Ahlijah, 2020; Osiobe et al., 2024a). Organizations must weigh these costs against the potential benefits and ensure that their investments in BI yield positive returns (Sahara & Aamer, 2022). Moreover, the success of BI initiatives depends heavily on the availability of skilled personnel with the technical expertise to interpret and analyze the data (Hatch & Buytendijk, 2010). MTN Nigeria, like many other organizations in the telecommunications sector, faces challenges in attracting and retaining professionals with the necessary BI expertise, particularly in a rapidly changing and increasingly complex business environment (IBM, 2011; McKinsey, 2011; Gartner, 2019; Osiobe, 2022). As companies continue to invest in BI, the demand for data scientists, analysts, and BI experts will only grow, making it essential for organizations to foster a culture of continuous learning and development (Srivastava & Bagga, 2014).

In Nigeria, the telecommunications sector has experienced remarkable growth, driven by increased mobile penetration, internet adoption, and evolving consumer preferences (Audzeyeva & Hudson, 2016; Osiobe, 2019b). To maintain their competitive edge, telecommunication companies like MTN Nigeria must leverage BI to make informed decisions about network infrastructure, customer satisfaction, and service offerings (Teoh, Binmoeller, & Lau, 2014). In doing so, they can address the growing complexity of their business environment and ensure operational efficiency (Laursen & Thorlund, 2016; Osiobe et al., 2019). However, the full potential of BI has yet to be realized due to persistent challenges related to data quality, integration, security, cost, and technical expertise (Kiron, Prentice, & Ferguson, 2014).

1.1. Statement of the Problem

The telecommunications industry in Nigeria, like in many parts of the world, is facing an increasingly complex and dynamic environment characterized by rapid technological advancements, globalization, and heightened competition (Tatić, Džafić, Haračić, & Haračić, 2018). For companies such as MTN Nigeria, effective decision-making is critical for sustaining competitive advantage and ensuring operational efficiency. However, the implementation of Business Intelligence systems in MTN Nigeria has been met with several significant challenges, including poor data quality, integration difficulties, data security vulnerabilities, high costs, and a shortage of technical expertise (Citaristi, 2022; Osiobe, 2020a).

Data quality issues have become a significant impediment to effective BI utilization at MTN Nigeria, where inconsistent, incomplete, or inaccurate data can lead to faulty insights and suboptimal decision-making (Rumisha et al., 2020; Osiobe, 2019b). A common example of this challenge is billing errors caused by flawed data, which not only harm customer satisfaction but also affect the company's revenue and reputation (Osiobe et al., 2024b). Similarly, data integration poses a considerable challenge as the disparate systems and formats used by MTN Nigeria make it difficult to create a cohesive and unified view of the data (Negro & Mesia, 2020; Osiobe et al., 2019). This lack of data integration hinders comprehensive analysis and the company's ability to perform holistic assessments (Osiobe et al., 2024c).

Data security is another critical challenge in the context of BI implementation at MTN Nigeria. The telecommunications industry is a prime target for cyberattacks, and any breach of sensitive customer information could result in severe financial and reputational damage (O'Loughlin et al., 2019; Osiobe, 2023). Furthermore, the high cost of implementing and maintaining BI systems has placed a significant strain on MTN Nigeria's budget, diverting resources from other critical areas such as network expansion and customer service improvements (Wahua & Ahlijah, 2020; Osiobe & Winingham, 2020). Finally, the shortage of skilled personnel with the necessary technical expertise to maximize the potential of BI systems further compounds these challenges (Hatch & Buytendijk, 2010; IBM, 2011; Osiobe, 2022).

1.2. Objectives of the Study

The main objective of this study is to assess the impact of Business Intelligence on organizational decision-making in the telecommunications industry, with a focus on MTN Nigeria. Specifically, the study seeks to:

1. Determine the extent of influence of data quality, data integration, data security, business intelligence cost, and technical expertise on service decision-making in MTN Nigeria.
2. Assess how data quality, data integration, data security, business intelligence cost, and technical expertise affect processing decision-making in MTN Nigeria.
3. Determine the impact of data quality, data integration, data security, business intelligence cost, and technical expertise on risk decision-making in MTN Nigeria.
4. Examine the influence of data quality, data integration, data security, business intelligence cost, and technical expertise on inventory decision-making in MTN Nigeria.
5. Assess the extent of impact of data quality, data integration, data security, business intelligence cost, and technical expertise on operational decision-making in MTN Nigeria.

2. Literature Review

2.1. Conceptual Review

Business Intelligence (BI) is a comprehensive concept that encompasses various activities, processes, and technologies aimed at gathering, storing, and analyzing information to improve organizational decision-making. Though BI has gained popularity in recent years due to advancements in analytics, big data, and artificial intelligence, it has a long history, borrowing from military and government administration, business management, and economics (Dishman & Calof, 2008; Maune, 2014). BI systems provide essential tools that enable organizations to assess internal and external environments, improving strategic, tactical, and operational decision-making (Søilen, 2015; Fourati-Jamoussi & Niamba, 2016). However, BI's true potential is realized only when the information it generates is effectively utilized to enhance business processes, products, and organizational agility (Jaklic, Grubljesic, & Popovic, 2018; Osiobe, 2020a). For companies like MTN

Nigeria, BI serves as an enabler that facilitates better decisions through a holistic approach, integrating various data sources and supporting long-term business growth (Larson & Chang, 2016; Osiobe, Winingham, & Olushola, 2019).

Data quality is a critical factor in BI implementation. High-quality data, characterized by accuracy, completeness, consistency, and relevance, is essential for informed decision-making (Isık et al., 2013). In the telecommunications industry, poor data quality can lead to significant operational inefficiencies, such as inaccurate billing and customer dissatisfaction. For instance, in MTN Nigeria, poor data quality could hinder customer service, network operations, and revenue management (Rumisha et al., 2020; Osiobe, 2020a). Additionally, data integration plays a pivotal role in ensuring the success of BI systems by combining diverse data sources to provide a unified view of organizational information (Wamba et al., 2017; Osiobe & Winingham, 2020). Effective data integration allows telecommunications companies to make better decisions based on comprehensive and synchronized information across departments (Popovič et al., 2012; Osiobe, 2019a).

On the other hand, data security remains a key concern, especially in cloud computing environments where unauthorized access or data breaches could lead to severe reputational and financial losses (NIST, 2018; Osiobe et al., 2024b). Ensuring confidentiality, integrity, and availability of data is essential for maintaining stakeholder trust and compliance with regulatory frameworks (Mahmood, 2011). Data security risks are particularly significant in industries handling sensitive customer information, such as telecommunications, making advanced security measures indispensable for BI success (Osiobe et al., 2024b).

The costs associated with BI implementation, including hardware, software, infrastructure, and human resources, are significant but often seen as a necessary investment for long-term success (Schryen, 2013). While the financial burden may strain resources, particularly for companies like MTN Nigeria, the return on investment from improved decision-making can offset these costs (Gartner, 2019; Osiobe, 2019a). In addition to cost, technical expertise is vital for optimizing BI systems. The shortage of skilled personnel in data analysis and BI tool management can hinder the full potential of BI adoption in the telecommunications sector (Kung Jr, 2008; Osiobe, 2021). Organizations need technically proficient staff who can extract valuable insights from BI systems and apply them in a way that enhances business outcomes (Schlee & Harich, 2010; Osiobe et al., 2024c). As telecommunications companies continue to adopt BI, their success will depend largely on balancing these factors—data quality, integration, security, cost, and technical expertise—to drive operational efficiency and sustain a competitive edge (Heskett, 1994; Osiobe, 2022).

2.2. Theoretical Review/Bases

The study is primarily grounded in The BI Maturity Model, a framework proposed by Dinter (2012), which is highly relevant for assessing the development and effectiveness of Business Intelligence (BI) systems within organizations. This model categorizes BI maturity into three dimensions—functionality, technology, and organizational—and provides a structured approach for evaluating how BI systems evolve over time (Dinter, 2012). As organizations progress through different levels of BI maturity, they improve their decision-making processes, with advanced BI systems enabling more data-driven, efficient, and strategic decision-making (Teoh, Rajendran, & Lim, 2014). The model also emphasizes the importance of aligning BI initiatives with broader business goals, ensuring that BI investments lead to enhanced organizational performance (Pejić Bach, Zoroja, & Čeljo, 2017). This theoretical framework will be essential in analyzing how MTN Nigeria has leveraged its BI capabilities to enhance decision-making processes, particularly in the telecommunications sector where data-driven strategies are increasingly critical for maintaining competitive advantage (Audzeyeva & Hudson, 2016).

In addition to the BI Maturity Model, the study integrates other supporting theories, such as the BI Competency Center (BICC) Model, which emphasizes the need for centralized BI management (Turban, Sharda, Aronson, & King, 2007), and Total Data Quality Management (TDQM) Theory, which focuses on the critical role of data quality in decision-making (Wang & Strong, 1996). The Information Systems Success Theory further strengthens the study by examining how system quality, information quality, and user satisfaction contribute to successful BI implementation (DeLone & McLean, 1992). Moreover, Enterprise Information Integration (EII) Theory addresses data integration across multiple systems (Lenzerini, 2002), while Defense in Depth Theory ensures that data security remains a priority in safeguarding valuable information. These complementary theories provide a comprehensive theoretical foundation for understanding how Business Intelligence can optimize decision-making, improve operational efficiency, and enhance the overall performance of MTN Nigeria.

2.3. Empirical Review

Drechsler (2014) emphasizes the benefits of BI adoption for SMEs, showcasing its positive impact on operational efficiency and strategic decision-making. Similarly, Hildebrandt (2012) highlights the importance of BI for SMEs, noting the challenges related to resource availability and technological readiness. Schellong explores BI usage in higher education, uncovering the potential for BI to improve institutional decision-making, while Tatić et al. (2018) emphasize the role of BI in SMEs in Bosnia and Herzegovina, where significant challenges like limited financial resources and insufficient expertise hinder the full adoption of BI systems. Moreover, Al-Nimer (2022) provides a study on the Jordanian telecommunications sector, demonstrating that the integration of BI leads to improvements in data quality and decision-making efficiency. In addition, Shollo (2013) investigates the impact of BI outputs on organizational decision-making, particularly in IT project prioritization processes.

The role of Data Quality, Data Integration, and Data Security in decision-making has been extensively explored in multiple studies, providing critical insights for the telecommunications sector. Mishra et al. (2013) and Chen et al. (2012) highlight how high-quality data improves decision-making by ensuring the accuracy, relevance, and timeliness of insights generated from BI systems. Meanwhile, Olszak & Bartu (2013) underscores the importance of BI in improving supply chain performance through enhanced data sharing and integration, while Yusof et al. (2022) investigate the potential of Native JSON as an innovative data integration model in BI applications. Furthermore, Niu et al. (2021) delve into the impact of Big Data Analytics (BDA) in organizations, highlighting its potential to improve decision-making processes by addressing challenges such as data quality and integration. In the realm of data security, Voloch et al. (2019) propose the Role and Trust-Based Access Control (RTBAC) model to mitigate privacy risks in online social networks, providing an example of how security frameworks can safeguard critical organizational data. Gao et al. (2020) present the Big Data Provenance Model (BDPM) for ensuring data security in big data environments, showing its relevance for enhancing the integrity of data in decision-making processes.

Furthermore, BI Costs and Technical Expertise remain key considerations in the adoption and successful implementation of BI systems. Wahua and Ahlijah (2020) assess the relationship between BI costs and performance in ECOWAS banks, revealing a negative impact on profitability when BI investments are not properly managed. Grytz and Krohn-Grimberghe (2018) examine stakeholders' perceptions of BI and analytics cost accounting, showing the need for greater transparency and better resource allocation in BI projects. Furthermore, studies like Cabero-Almenara et al. (2019) emphasize the need for technical expertise to fully leverage the potential of BI systems, a sentiment echoed by Lavazza and Farina (2020) in the context of expert-driven decision-making during the COVID-19 pandemic. The importance of technical skills is also highlighted by Bickley et al. (2021), who discuss how emerging technologies like quantum computing could revolutionize decision-making processes by enhancing analytical capabilities. Ultimately, the empirical review underscores the need for comprehensive BI systems, robust data quality, effective integration, strong data security, and technical expertise to drive impactful decision-making in telecommunications companies like MTN Nigeria.

3. Methodology

3.1. Research Design

The research design for this study is based on a mixed-method approach, incorporating both survey and case study strategies to explore the impact of Business Intelligence (BI) on organizational decision-making within MTN Nigeria. As stated by Agu (2017), research design forms the foundation of a study, detailing the plan and methods that guide the research process. The survey design was utilized to collect quantitative data from a selected sample size, while the case study design focused specifically on MTN Nigeria, providing an in-depth examination of the relationship between BI components—such as data quality, integration, security, cost, and technical expertise, and decision-making processes like service, risk, inventory, and operational decisions. This combination of designs enabled a comprehensive and well-rounded understanding of BI's role within MTN Nigeria.

3.2. Population of the Study

The study's population consisted of 1495 employees of MTN Nigeria across various zonal offices, retail outlets, and service centers. These employees included financial experts, ICT professionals, business strategists, human resources personnel, quality assurance officers, engineers, and senior management. The stratified random sampling technique was adopted to ensure proportional representation from all departments and locations. The sample included various departments to capture a comprehensive range of perspectives concerning BI's role in decision-making processes. The target population was divided into strata based on department and location, enabling the study to generalize its findings to the entire organization.

3.3. Sample Size Calculation

The sample size for the study was calculated using Taro Yammane's formula, which is widely accepted in statistics and management research. Given the total population of 1495 employees, the formula is expressed as:

By the Yamane formulae is set as:

$$n = N \Big/ \left(1 + N\left(e\right)^{2}\right) \tag{3.1}$$

where:

n represented the computed sample size; N represented the population size of stakeholders and management employees of MTN Nigeria. (MTN) at the various selected states (i.e., 1495); he represented the acceptable sampling error, and this is 5% assumed.

Thus,

n = 1495/1 + 1495(0.05)^2

n = 1495/4.7375

n = 315.567 respondents.

Thus, the sample size for the study was determined to be 316 respondents.

3.4. Sample Size Distribution

The stratified random sampling technique was employed to ensure that the various departments and locations were proportionally represented. This shows the distribution of the sample size across different locations and departments within MTN Nigeria (Table 1):

Table 1. Sample size distribution.

Location	Financial Expert	Internal Audit	ICT Expert	Business/ Strategic	HR Expert	Quality Personnel	Engineers	Senior Mgt	Others	Total Sample
Abia	2	1	3	1	1	2	4	1	0	15
Delta	1	1	2	1	1	1	4	2	0	13
Edo	2	1	3	1	1	3	6	1	1	20
Ekiti	2	1	2	1	1	2	4	2	0	15
Enugu	2	1	2	1	1	1	3	1	0	11
FCT	4	2	5	2	2	3	8	3	2	30
Kaduna	3	2	4	1	1	4	6	2	0	23
Kwara	2	1	3	1	1	2	5	2	0	18
Lagos	7	4	21	3	5	6	15	10	6	78
Ogun	2	1	3	1	1	1	3	3	1	16
Oyo	2	1	4	1	1	2	5	3	1	20
Plateau	3	1	3	1	1	1	4	2	1	17
Rivers	5	2	7	3	3	4	12	4	1	40
Total	36	19	62	18	21	31	79	37	14	316

Source: Online Survey (2023).

3.5. Validity and Reliability Test

To ensure the validity and reliability of the study instrument, a rigorous process was followed. The content and face validity of the questionnaire were assessed by distributing it to subject matter experts and scholars from outside the study population. This review process allowed the experts to examine the questionnaire and provide feedback on its structure, content, language, and relevance to the variables of interest. Adjustments were made to enhance the clarity and focus of the questions, ensuring that the instrument accurately measured the constructs relevant to the study.

The reliability of the questionnaire was assessed using Cronbach's Alpha, a widely accepted measure of internal consistency. Cronbach's Alpha provides an estimate of how consistently the items in a questionnaire measure a construct. A higher Cronbach's Alpha value indicates greater reliability of the scale. The formula for Cronbach's Alpha is given as:

$$\alpha = \left(N \cdot c^{-}\right) / \left(v^{-} + \left(N - 1\right) \cdot c^{-}\right) \quad (3.2)$$

where:

- N is the number of items,
- $\bar{c}$ is the average covariance between item pairs,
- $\bar{v}$ is the average variance.

The reliability of the study instrument was found to be excellent, with Cronbach's Alpha values above 0.8 for all the variables, indicating that the instrument was highly reliable. The reliability results for Business Intelligence, Data Quality, Data

Integration, Data Security, Business Intelligence Cost, and Technical Expertise were 0.969, 0.889, 0.949, 0.902, 0.871, and 0.939, respectively. These values suggest that the study instrument consistently measures the constructs of interest and ensures valid inferences can be drawn from the data.

3.6. Method of Data Analysis

The study employed Structural Equation Modeling (SEM) using Smart PLS to analyze the relationships between Business Intelligence and organizational decision-making. SEM is a multivariate statistical analysis technique that simultaneously assesses the relationships between observed and latent variables. It combines factor analysis and multiple regression to model complex relationships and is ideal for validating measurement models and testing hypotheses related to the structural model.

3.6.1. Measurement Model

The measurement model in SEM establishes the relationship between observed indicators and latent variables (e.g., Data Quality, Data Integration, etc.). This relationship is represented by the following equations:

$$x = \Lambda_x \xi + \delta \tag{3.3}$$

$$y = \Lambda_y \eta + \in \tag{3.4}$$

where:

- x and y are vectors of observed exogenous and endogenous variables,
- ξ and η are the exogenous and endogenous latent variables,
- Λ_x and Λ_y are the factor loading matrices,
- δ and ϵ are the measurement errors.

3.6.2. Structural Model

The structural model captures the relationships between latent variables (e.g., Business Intelligence components and organizational decision-making outcomes). The general structural model is represented as:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{3.5}$$

where:

- η represents endogenous latent variables (organizational decision-making proxies),
- ξ represents exogenous latent variables (Business Intelligence proxies),
- B is the coefficient matrix for relationships among endogenous variables,
- Γ is the coefficient matrix for relationships between exogenous and endogenous variables,
- ζ is the error term.

The variance-covariance matrix for the structural model is derived as:

$$\Sigma = \Lambda_y \left(I - B\right)^{-1} \Gamma \Lambda_x^T + \Theta_\delta \tag{3.6}$$

3.6.3. Path Coefficients and Model Fit

The path coefficients ($\hat{\beta}$) estimate the strength of the relationships between latent variables and are computed as:

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T Y \tag{3.7}$$

Where:

- X is the matrix of independent latent variables,
- Y is the matrix of dependent latent variables.

The overall model fit was assessed using standard SEM fit indices such as the Chi-Square statistic, Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) to ensure the robustness of the model. These indices help validate the SEM model by ensuring that the hypothesized relationships are consistent with the data.

3.7. Model Specification

For this study, the relationship between the independent variables (Business Intelligence components) and the dependent variables (organizational decision-making proxies) is specified as follows:

$$SD = \beta_0 + \beta_1 DQ + \beta_2 DI + \beta_3 DS + \beta_4 BIC + \beta_5 TE + \in \tag{3.8}$$

$$PD = \beta_0 + \beta_1 DQ + \beta_2 DI + \beta_3 DS + \beta_4 BIC + \beta_5 TE + \in \tag{3.9}$$

$$RD = \beta_0 + \beta_1 DQ + \beta_2 DI + \beta_3 DS + \beta_4 BIC + \beta_5 TE + \in \tag{3.10}$$

$$ID = \beta_0 + \beta_1 DQ + \beta_2 DI + \beta_3 DS + \beta_4 BIC + \beta_5 TE + \in \tag{3.11}$$

$$OD = \beta_0 + \beta_1 DQ + \beta_2 DI + \beta_3 DS + \beta_4 BIC + \beta_5 TE + \in \tag{3.12}$$

where:

SD = Service Decision,
PD = Processing Decision,
RD = Risk Decision,
ID = Inventory Decision,
OD = Operational Decision,
DQ = Data Quality,
DI = Data Integration,
DS = Data Security,
BIC = Business Intelligence Cost,
TE = Technical Expertise,
β_0 to β_5 are parameters to be estimated,
ϵ is the error term.

The SEM approach implemented in Smart PLS effectively examines the direct and indirect relationships between these variables, allowing for a comprehensive analysis of the impact of Business Intelligence on organizational decision-making within MTN Nigeria.

4. Results

4.1. Respondents Demographics

The demographic characteristics of the respondents were analyzed thus providing insights into their gender distribution, educational qualifications, years of experience, and departmental affiliations. A higher percentage of the respondents were male (63%) compared to female (37%), indicating a gender disparity among employees. Regarding educational qualifications, the majority of the respondents held a Master's degree (41.5%), followed by those with Bachelor's degrees (34.2%). A significant number also had doctorate degrees (19%), while only a small portion of the respondents held an HND qualification (2.8%), and 2.5% did not respond. In terms of work experience, the largest group of employees had between 5 to 10 years of experience (65.8%), while 13.3% had 11 to 20 years, and 20.9% had over 21 years of experience, reflecting a diverse range of expertise within the workforce. The departmental distribution showed that the Engineering Department (17.7%) had the highest representation, followed by ICT (15.8%), HR (10.8%), and Operations (10.4%). Other departments such as Business/Strategic, Customers Experience, Internal Audit, and Network Operations each contributed smaller percentages, with fewer employees from the Sales, Office of the CEO, and Finance departments. This diversity in both experience and departmental representation offers a broad perspective on the organizational decision-making processes being studied.

4.2. Model Estimation

The path coefficient analysis in **Table 2** presents a strong and statistically significant relationship between Business Intelligence (BI) and Organizational Decision Making (ODM), with a path coefficient of 0.741, indicating a robust positive association between these variables. The small standard deviation (0.025) suggests consistent results across the sample. The high T-statistic of 29.761 and a *p*-value of 0.000 reinforce the significance of this relationship, allowing for the confident rejection of the null hypothesis that there is no connection between BI and ODM. These findings are consistent with previous research that highlights the crucial role of BI in enhancing decision-making processes (Khong et al., 2023; Sahara & Aamer, 2022). Specifically, within the telecommunication sector, focusing on BI initiatives can substantially improve decision-making outcomes, underscoring the importance of strategic investment in BI to optimize decision-making and enhance operational efficiency.

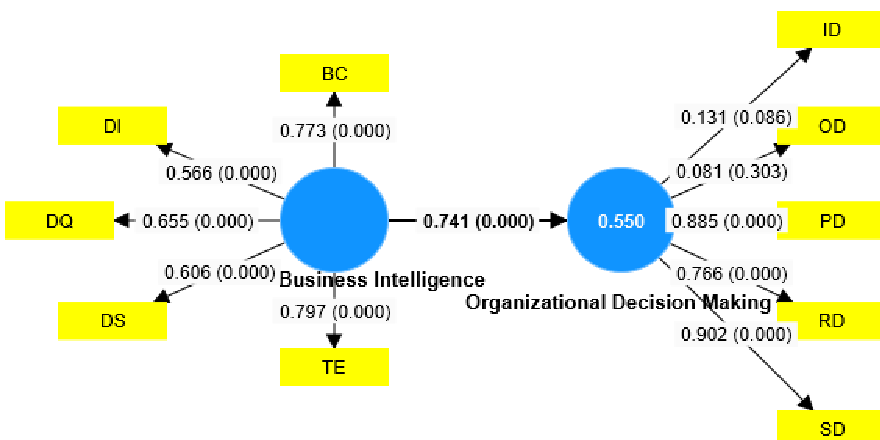

Figure 1. Overall model PLS-SEM.

Table 2. Over-all path coefficients (Mean, STDEV, T Values, P Values).

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Business Intelligence -> Organizational Decision Making	0.741	0.746	0.025	29.761	0.000

Source: Smart-PLS 4 Output, 2024.

Table 3. Outer loadings (Mean, STDEV, T Values, P Values).

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BIC <- Business Intelligence	0.773	0.772	0.036	21.259	0.000
DI <- Business Intelligence	0.566	0.561	0.070	8.034	0.000
DQ <- Business Intelligence	0.655	0.650	0.064	10.235	0.000
DS <- Business Intelligence	0.606	0.600	0.077	7.839	0.000
ID <- Organizational Decision Making	0.131	0.132	0.077	1.716	0.086
OD <- Organizational Decision Making	0.081	0.084	0.079	1.031	0.303
PD <- Organizational Decision Making	0.885	0.885	0.013	67.696	0.000
RD <- Organizational Decision Making	0.766	0.763	0.039	19.732	0.000
SD <- Organizational Decision Making	0.902	0.901	0.012	72.809	0.000
TE <- Business Intelligence	0.797	0.800	0.025	32.521	0.000

Source: Smart-PLS 4 Output, 2024.

The outer loadings analysis on Table 3 reveals a strong and statistically significant relationships between the latent constructs and their observed indicators. Notably, the outer loading for the "BIC <- Business Intelligence" indicator was 0.773, with a T-statistic of 21.259 and a *p*-value of 0.000, indicating a robust relationship. Results are also presented in Figure 1. These results demonstrate the significant contribution of Business Intelligence (BI) to Business Cost (BC). Similarly, the other Business Intelligence indicators, such as data integration, data quality, data security, and technical expertise, show strong and significant relationships, supporting literature emphasizing the role of BI in organizational decision-making (Sahara & Aamer, 2022; Khong et al., 2023). Furthermore, the Organizational Decision-Making indicators, including processing, risk, and service decisions, exhibit strong outer loadings, particularly for Processing Decision (PD), Risk Decision (RD), and Service Decision (SD), highlighting the critical influence of BI on decision-making, consistent with prior studies (Sahara & Aamer, 2022).

Model Performance Diagnostic Tests

The model's performance was assessed using several diagnostic tests to ensure its

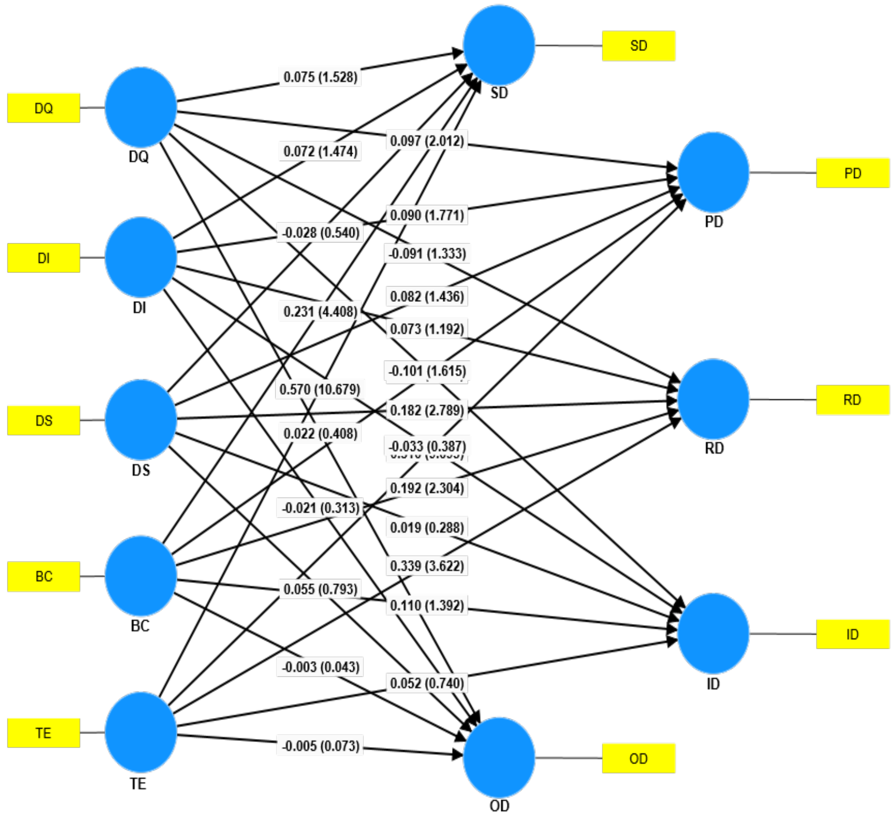

Figure 2. Path for study variables interactions.

validity and fit. The Heterotrait-Monotrait (HTMT) ratio was 0.819, below the recommended threshold of 0.85, confirming discriminant validity between the constructs of Business Intelligence and Organizational Decision-Making. This suggests that the two constructs are distinct and not measuring the same underlying concept, as supported by Hair et al. (2017). The Fornell-Larcker criterion further confirmed discriminant validity, as the square roots of the Average Variance Extracted (AVE) were greater than the inter-construct correlations, indicating that each construct shares more variance with its indicators than with other constructs. Additionally, Variance Inflation Factor (VIF) values were below the threshold of 5, demonstrating that multicollinearity is not a concern, which strengthens the reliability of the estimated relationships (Hair et al., 2017). Regarding model fit, the SRMR of 0.125, d_ULS of 0.860, and d_G of 0.255 indicate a reasonable fit, although the Chi-square value of 442.493 and the NFI of 0.631, while acceptable, require cautious interpretation due to sensitivity to sample size (Kline, 2015). The Bayesian Information Criterion (BIC) for Organizational Decision-Making was −241.683, suggesting a strong fit, as lower BIC values indicate a better model. Collectively, these diagnostics support the adequacy of the structural equation model in explaining the relationships between Business Intelligence and Organizational Decision-Making in MTN Nigeria, consistent with findings from the literature (Sahara & Aamer, 2022; Khong et al., 2023; Gebreslassie et al., 2023).

4.3. Discussion of Findings

H_{01}: Impact of Data Quality, Data Integration, Data Security, Business Intelligence Cost, and Technical Expertise on Service Decision in MTN Nigeria

The analysis of the impact of Business Intelligence Cost (BIC) on Service Decision (SD) presented in **Figure 2** revealed a significant relationship, with a path coefficient mean of 0.231, a t-statistic of 4.408, and a *p*-value of 0.000. This leads to the rejection of the null hypothesis (H01), indicating that Business Intelligence Cost significantly influences service decisions. The findings are consistent with Wixom and Watson (2010), who emphasize the role of investment in business intelligence for more effective service-related decisions. Conversely, Data Integration (DI) and Data Quality (DQ) did not exhibit significant impacts on service decision-making, with *p*-values of 0.140 and 0.127, respectively. This suggests that while data integration and quality are important, they may not directly influence service decisions in MTN Nigeria (Chen et al., 2021; Wang et al., 2019). Similarly, Data Security (DS) did not show a significant effect on service decisions, aligning with Wang et al. (2019), who highlight the complex implications of security in decision-making. However, Technical Expertise (TE) was found to have a significant positive impact on service decisions, with a path coefficient mean of 0.570, t-statistic of 10.679, and a *p*-value of 0.000, supporting Wang and Strong's (1996) findings on the importance of technical skills in business intelligence for effective service decisions.

H_{02}: Influence of Data Quality, Data Integration, Data Security, Business Intelligence Cost, and Technical Expertise on Processing Decision in MTN Nigeria

Business Intelligence Cost (BIC) on **Figure 2** had a statistically significant influence on Processing Decision (PD) with a path coefficient mean of 0.116, a t-statistic of 2.188, and a *p*-value of 0.029. This leads to the rejection of the null hypothesis, suggesting that BI cost considerations are critical in processing-related decisions, as supported by Han et al. (2016). Data Integration (DI), however, did not show a significant impact on processing decisions, with a *p*-value of 0.077, indicating a context-dependent relationship (Chen et al., 2021). Data Quality (DQ) also exhibited a significant influence on processing decisions, with a *p*-value of 0.044, aligning with Wang et al. (2019), who emphasize the importance of data quality in decision-making. Data Security (DS) did not significantly affect processing decisions, with a *p*-value of 0.151, supporting previous findings on the nuanced role of security in processing decisions (Wang et al., 2019). Lastly, Technical Expertise (TE) significantly impacted processing decisions, with a t-statistic of 9.693 and a *p*-value of 0.000, reaffirming the role of expertise in enhancing decision outcomes (Wang & Strong, 1996).

H_{03}: Association Between Data Quality, Data Integration, Data Security, Business Intelligence Cost, Technical Expertise, and Risk Decision in MTN Nigeria

Business Intelligence Cost (BIC) in **Figure 2** demonstrated a significant association with Risk Decision (RD), as the path coefficient mean was 0.192, with a t-statistic of 2.304 and a *p*-value of 0.021, confirming that financial considerations influence risk-related decisions in MTN Nigeria (Power, 2009). However, Data Integration (DI) and Data Quality (DQ) did not significantly affect risk decisions, with *p*-values of 0.233 and 0.183, respectively, indicating a weaker connection between these BI factors and risk management (Jain et al., 2018; Watson, 2017). In contrast, Data Security (DS) had a significant effect on risk decision-making, with a t-statistic of 2.789 and a *p*-value of 0.005, highlighting the critical role of data protection in risk management (Chen et al., 2021). Technical Expertise (TE) also showed a strong positive influence on risk decisions, with a path coefficient mean of 0.339, a t-statistic of 3.622, and a *p*-value of 0.000, reinforcing the findings of Power (2009) regarding the importance of technical know-how in navigating risk-based decisions.

H_{04}: Impact of Data Quality, Data Integration, Data Security, Business Intelligence Cost, and Technical Expertise on Inventory Decision in MTN Nigeria

Business Intelligence Cost (BIC) in **Figure 2** did not show a statistically significant impact on Inventory Decision (ID), with a path coefficient of 0.11, a t-statistic of 1.392, and a *p*-value of 0.164. This leads to the failure to reject the null hypothesis, indicating that the cost of business intelligence does not significantly affect decisions concerning inventory levels in MTN Nigeria. This is consistent with Petersen et al. (2015), who suggested that the relationship between business intelligence costs and inventory decisions can be context-dependent and complex. Similarly, Data Integration (DI) and Data Quality (DQ) also showed no significant impact on inventory decisions, with *p*-values of 0.699 and 0.106, respectively. These findings align with literature emphasizing the nuanced role of data in decision-making and inventory management (Chen et al., 2021; Wang et al., 2019). Data Security (DS) did not demonstrate a significant effect on inventory decision-making, with a t-statistic of 0.288 and a *p*-value of 0.773, indicating that security concerns may not play a central role in inventory decisions (Wang et al., 2019). Technical Expertise (TE) similarly showed no significant impact, with a t-statistic of 0.740 and a *p*-value of 0.459, suggesting that while technical skills are essential, they may not directly influence inventory decisions (Wang & Strong, 1996).

H_{05}: Impact of Data Quality, Data Integration, Data Security, Business Intelligence Cost, and Technical Expertise on Operational Decision in MTN Nigeria

The analysis of Business Intelligence Cost (BIC) in **Figure 2** in relation to Operational Decision (OD) revealed no significant impact, with a path coefficient mean of -0.003, a t-statistic of 0.043, and a *p*-value of 0.966. This implies that business intelligence costs do not significantly influence operational decisions in MTN Nigeria, aligning with findings in the literature that highlight the complex and context-specific nature of cost in operational decision-making (Li et al., 2019). Similarly, Data Integration (DI) and Data Quality (DQ) did not significantly affect operational decisions, with *p*-values of 0.754 and 0.683, respectively. These results indicate that neither the integration nor the quality of data plays a central role in operational decisions at MTN Nigeria, supporting studies by Chen et al. (2021) and Wang et al. (2019) that emphasize the multifaceted and context-dependent impact of data factors on operational outcomes. Data Security (DS) also did not have a statistically significant impact, with a p-value of 0.428, suggesting that data security measures are less influential in operational decision-making processes (Wang et al., 2019). Finally, Technical Expertise (TE) also showed no significant impact on operational decisions, with a p-value of 0.942, reinforcing findings from Wang and Strong (1996) that highlight the importance of technical expertise but also its varying influence across different decision-making domains.

5. Conclusion

5.1. Summary

This study explored the impact of various components of Business Intelligence (BI), including data quality, data integration, data security, business intelligence cost, and technical expertise, on different dimensions of organizational decision-making in MTN Nigeria. The findings showed that certain aspects of BI, such as business intelligence cost and technical expertise, have a significant impact on service, processing, and risk-related decisions, highlighting the importance of investing in BI systems and ensuring the availability of skilled personnel to enhance decision-making. However, the study also revealed that data quality, data integration, and data security do not consistently exert a significant influence across all decision domains, particularly in inventory and operational decision-making. The results align with existing literature emphasizing the context-dependent nature of BI components in decision-making processes (Wang & Strong, 1996; Wixom & Watson, 2010). While BI systems can enhance the effectiveness of decision-making, the impact varies based on the decision type and organizational priorities (Power, 2009; Han et al., 2016). For instance, studies have shown that the influence of BI on service decisions differs from its effect on processing or risk-related decisions, highlighting the multifaceted role BI plays in various decision domains (Chen et al., 2021; Jain et al., 2018). The study highlights the need for MTN Nigeria to tailor its BI strategies to the specific needs of each decision-making area, ensuring that resources are allocated effectively to maximize the value derived from BI investments (Sahara & Aamer, 2022; Khong et al., 2023). This approach is consistent with the literature on adaptive BI strategies, which stresses the importance of aligning BI initiatives with organizational goals to optimize decision-making outcomes (Gebreslassie et al., 2023; Li et al., 2019).

5.2. Recommendations

i. MTN Nigeria should continue investing in business intelligence systems, particularly focusing on enhancing technical expertise among employees, as it significantly influences key decision areas.
ii. The company should explore ways to improve data integration processes, even though its impact on certain decision areas like service and inventory was found to be minimal, to ensure seamless data flow across the organization.
iii. MTN Nigeria should prioritize data quality in operational decision-making

processes by implementing more stringent data governance and management practices.

iv. Given the minimal impact of data security on decision-making, the company should focus on adopting a more comprehensive approach to integrating security with decision-making tools to protect data integrity and confidentiality.

v. MTN Nigeria should consider reevaluating its BI cost structure to ensure that investments in BI tools are directly aligned with the company's strategic decision-making goals, optimizing returns on BI expenditures.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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