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Data Analytics and Efficiency of Public Hospitals in Rivers State, Nigeria

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***Abstract**: This study examined the relationship between data analytics and efficiency of public hospitals in Rivers State, Nigeria. The study adopted the cross-sectional survey in its investigation of the variables. Primary source of data was generated through self- administered questionnaire. The population of the study was 810 employees of the 20 public hospitals in Rivers State, from which a sample of 265 employees was determined using the Krejcie and Morgan (1970) table. The reliability of the instrument was achieved by the use of the Cronbach Alpha coefficient with all the items scoring above 0.70. Data generated were analyzed and presented using both descriptive and inferential statistical techniques. The hypotheses were tested using the Spearman Rank Order Correlation Coefficient. The tests were carried out at a 95% confidence interval and a 0.05 level of significance. A total number of 265 copies of the questionnaire was administered to the respondents and 221 which represents approximately 83.40% were returned and found usable for the analysis. The findings revealed that there is a significant relationship between data analytics and efficiency of public hospitals in Rivers State, Nigeria. The study recommends that public hospitals should consider incorporating descriptive analytics practices into their operations. This involves collecting and analysing historical data on patient flow, resource allocation, operational processes, and healthcare outcomes.*

***Keywords:** Data Analytics, Efficiency, Public Hospitals*

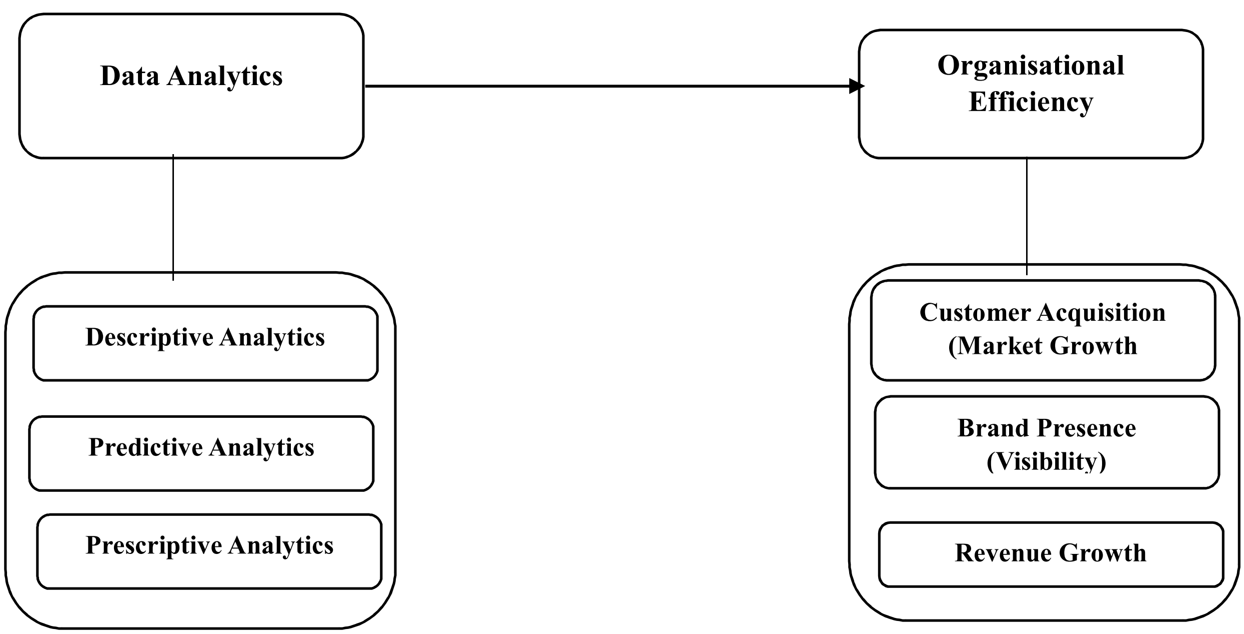
Introduction

Data analytics is a crucial component in today's business landscape, providing valuable insights that drive informed decision making. From optimizing operations to enhancing customer experience, the importance of data analytics cannot be overstated. Firstly, data analytics plays a pivotal role in business decision making, enabling organizations to identify trends, patterns, and correlations that would otherwise go unnoticed. Secondly, data analytics enhances customer experience by analyzing vast amounts of data to personalize interactions, anticipate needs, and deliver tailored solutions. Lastly, ethical considerations surrounding data analytics and privacy protection are vital to ensure the responsible and secure use of customer data. In conclusion, data analytics empowers businesses to make strategic decisions, improve customer satisfaction, and uphold ethical standards in the digital age.

Data analytics plays a crucial role in business decision making, as it allows organizations to extract valuable insights from large volumes of data to inform strategic choices and optimize performance. According to Alsghaier, Akour, Shehabat, and Al-Kilani (2017), data analytics assists businesses in identifying patterns, trends, and correlations in data sets, enabling them to understand customer behavior, predict market trends, and identify potential opportunities or risks. By analyzing historical data, companies can gain a deeper understanding of their customers' preferences, buying patterns, and needs, which can inform product development, marketing strategies, and customer relationship management. Moreover, data analytics can help businesses monitor and evaluate the effectiveness of their operations, allowing them to identify inefficiencies, streamline processes, and improve productivity. By leveraging data analytics, organizations can make data-driven decisions, enhance operational efficiency, and gain a competitive advantage in the market.

Data analytics plays a crucial role in improving customer experience. According to Holmlund Van Vaerenbergh, Ciuchita, Ravald, Sarantopoulos, Ordenes and Zaki (2020), data analytics enables businesses to gain valuable insights into customer behavior, preferences, and needs. By analyzing large volumes of data, organizations can identify patterns and trends that help them understand customer expectations and tailor their products or services accordingly. This allows businesses to deliver personalized experiences that resonate with customers, leading to increased satisfaction and loyalty. Moreover, data analytics helps companies identify pain points in the customer journey and make informed decisions to address them. By analyzing customer feedback and sentiment data, organizations can identify areas of improvement and implement targeted strategies to enhance the overall customer experience. In addition, data analytics enables organizations to measure and track key performance indicators (KPIs) related to customer experience, such as Net Promoter Score (NPS) or Customer Satisfaction (CSAT). This allows businesses to assess the effectiveness of their initiatives and make data-driven decisions to continuously enhance the customer experience. Therefore, data analytics plays a pivotal role in improving customer experience by providing valuable insights, enabling personalized experiences, identifying pain points, and measuring performance indicators. (Holmlund *et al.* 2020). The purpose of this paper is to data analytics and efficiency of public hospitals in Rivers State, Nigeria.

Research Conceptual Model



Source: Author’s Research Model (2023)

The study tested the following hypotheses for validation or refutation:

Ho1: There is no significant relationship between descriptive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Ho2: There is no significant relationship between predictive analytics and efficiency of public hospitals in Rivers State, Nigeria

Ho3: There is no significant relationship between prescriptive analytics and efficiency of public hospitals in Rivers State, Nigeria

Literature Review

Theoretical Foundation

Adaptive Structuration Theory (AST)

Adaptive Structuration Theory (AST) was propounded by Gerardine *DeSanctis* and Marshall Scott *Poole* in 1994. It assumes that information systems and organizations are interrelated. Adaptive Structuration Theory (AST) is relevant to today's organizations due to the expanding influence that advancing technologies have had with regard to the human-computer interaction aspect of AST and its implications on socio-biologically inspired structuration in security software applications. AST provides the model whereby the interaction between advancing information technologies, social structures, and human interaction is described, and which focuses on the social structures, rules, and resources provided by information technologies as the basis for human activity. Adaptive Structuration Theory views organizations as systems of communication. When individuals desire to create a group, they begin by communicating. The individuals express their expectations for the group, and soon a set of rules, or structure, begins to emerge. The individuals establish the group by accepting the rules. As group members continue to communicate in the course of making decisions, weaknesses or limitations in the structure become apparent. Group members then modify the rules to better suit their needs. As members change, draw upon new resources to solve problems or experience shifts in environment, the group attempts to maintain stability by altering its structure.

In this way, AST shows how communication allows groups to evolve while remaining stable. Indeed, without communication, organizations would cease to exist. This theory is formulated as the production and reproduction of the social systems through members' use of rules and resources in interaction. DeSanctis and Poole (1994) adapted Giddens theory to study the interaction of groups and organizations with information technology, and called it Adaptive Structuration Theory. AST criticizes the techno centric view of technology use and emphasizes the social aspects. Groups and organizations using Information Technology for their work dynamically create perceptions about the role and utility of the technology, and how it can be applied to their activities. These perceptions can vary widely across groups. These perceptions influence the way human resource management information system is used and hence mediate its effect on organization performance.

Data Analytics

According to Handa and Garima (2014) data analytics refers to the use of both qualitative and quantitative data to gain insights and support people management through effective decision-making processes. Data analytics simply is collecting, manipulating, and reporting data through the use of information technology. Heuvel and Bondarouk (2017) also posit that data analytics is about identifying and quantifying people drivers systematically for better decision making on business outcomes. This means that, being able to analyse data related to human resources to make decisions in a systematic way.

Davenport and Harris and Shapiro (2007) describe big data analytics as the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions". In other words, the raw material here is data, which is processed using a multitude of statistical methods, and what is happening at organizational level is that a new style of management is put in place, which is based on evidence, contrary to the so called "gut feeling" decisions or managing by one's experience. Based on the scope, big data analytics, can be classified as: descriptive analytics, predictive analytics and prescriptive analytics (Davenport & Kim, 2013). These three dimensions answer the following questions: "what happened?", "what is probable to happen?", "what should we do about it?". Because data analytics are used to make decisions to improve both individual and organisational performance, it should focus on the future rather than the past (Smeyers, 2012). Although HR analytics is growing at a speed rate, some firms are still struggling to implement it due to the major capability gap found in today's business practice (Deloitte, 2015; 2016; 2017).

Dimensions of Data Analytics

Descriptive Analytics

Descriptive analysis is the first type of data analytics (Fitz-enz, 2010) and this is used to understand past behaviours and outcomes and also to help examine and describe the relationships and patterns that exist between them (Ulrich & Dulebohn, 2015). At this level, it is more of cost reduction and total process improvement (Fitz-enz & Mattox, 2014). It helps to answer the question, "What happened?" The descriptive analysis involves the use of published reports, dashboards/scorecards, data visualization and basic data mining (Fitz-enz & Mattox, 2014). Due to the nature of the descriptive level analysis, it does not attach meanings to patterns observed. This is more exploratory than predictive (Narula, 2015) and so users need to be careful not to make predictions into the future with this data as this may be risky to the organisation. This is because the main aim is to understand the present from the past.

The type of question answered, data focused on and the endowment to generate worth for business makes a difference between the four types of analytics. Descriptive analytics focuses on the past to make an informed decision (Naasz & Nadel, 2015), and it is more concerned with differences and relationships between different groups. According to Ranjan and Basak (2013), the most accessible type of analytics is descriptive analytics. It uses raw data that were derived from various sources to give a good insight into the past. The technology that is being utilized is secure, but advanced statistical tools are needed in the process. "what happened?" is the question that is tried to be answered by this type of analytics. Ruohonen (2015) stated that the main characteristics of descriptive analytics are describing the historical and current patterns of data and events, the focus of process improvement and cost reduction and visualization format; scorecards and dashboards.

Predictive Analytics

The second level or type of data analytics is predictive analysis. At this level of analysis, the meaning is given to the data to make projections into the future. Predictive analytics is the application of statistical and forecasting models to past and present data to make predictions regarding future occurrences (Reddy & Lakshmikeerthi, 2017). According to Fitz-enz (2009), with practice, there is the likelihood that, future occurrences to some degree can be made through the analysis of historical data. That is, the predictive analysis is more focused on probabilities and potential impact (Fitz-enz & Mattox, 2014) and answers the question, "Why did it happen?" According to Watson (2014), predictive analysis can be used to identify attributes that are required to increase job performance and is able to screen suitable applicants for the job. Simulation models can be used to evaluate job demand and supply using for example, "Java Developers" and as work conditions change, the models are rerun to update both hiring and retention plans (Narula, 2015). Some forms of predictive analysis are genetic algorithms, neural networks, decision trees (Watson, 2014; Narula, 2015). According to Bersin (2013) as cited in Narula 2015), only 4% of companies have been able to reach the level of performing predictive analytics on their workforce. According to Mishra, Lama, and Pal (2016), predictive analytics has been able to provide organisations with insights into data to enhance future predictions. This level of analysis goes beyond mere data presentations on reports, tables or metrics but rather a proactive strategy to improve people-related decisions (Mishra, Lama, & Pal, 2016). Techniques such as data mining have become popular in this area as it seeks patterns from large organisational data set. It is able to answer the questions of "where will it happen again and in what magnitude".

Data analytics plays a role in every aspect of the organisational function, including recruiting, training and development, succession planning, retention, engagement, compensation, and benefit (Mishra, Lama & Pal, 2016). Predictive HR analytics (PHRA) emanates from the ability of data to "Predict" what might happen in the future, it understands the future. It is not like the descriptive analytics that focuses on mere reactive data presentations on tables, reports, metrics or dashboards; it is a proactive data-driven insights that facilitate better people-related decisions (Mishra *et al.*, 2016). It involves statistical techniques and data mining models that mine and evaluate existing or historical data to pick out trends and make future predictions. It enables organizations to analyse the past and look forward to spot trends in key factors related to managing human capital and other sources of risk. Mishra *et al.* (2016) emphasized that predictive analytics provides organisations with actionable view or insights into data and give the decision maker an idea about the likelihood of a future outcome.

Mishra, *et al.* (2016) emphasized that PHRA provides organisations with actionable view or insights into data and give the decision maker an idea about the likelihood of a future outcome. Even though no statistical algorithm can actually give a 100% certainty of the future outcome, the PHRA uses data to establish the most likely future outcome of an event or the likelihood of a situation happening. PHRA combines historical data to recognize trends and apply statistical models to know the relationships between and amongst arrays of data. HR practitioners and Organizations use predictive statistics and analytics to see the future.

Different types of analytics are required and frequently used to determine the ingredients of substantial business outcomes with regards to the business setting. For example, banks use predictive approach to understand consumer behaviour. It can also be used in HRM practice to predict employee retainability which can inform succession planning decisions. These approaches make a knowledgeable, predictive assessment based on facts and data. Examples of PHRA are; no of error versus skill level, cost of error versus cost of training, last month attrition rate versus present month attrition rate etc. As earlier established, PHRA extends the questions that descriptive analytics is answering to the next level by moving from a retrospective set of answers to a set of answers focused on predicting performance and laying down detailed action plans or recommendations. Sesil (2013) established that PHRA has aided practitioners to achieve organizational objectives through HR management, workforce planning, employee management, and performance management etc.

Prescriptive Analytics

The third and highest level of data analytics is prescriptive analysis. It focuses more on complex data that is used to make improved decisions. This form of analysis examines data and is able to answer the question "what should be done?" or "how can we make it happen?" The prescriptive analysis enables organisations to make accurate predictions about their workforce such as a possible employee resignation (Jensen-Eriksen, 2016). Mathematical programming and simulation are some examples of prescriptive analysis. It is worth emphasizing that, prescriptive analytics go beyond predictions as it uses high-quality statistics to make an influence on businesses. It is a more advanced form of predictive analytics that combines optimization techniques with statistical analysis to provide for uncertainty in the data (Kapoor & Kabra, 2014). Ranjan and Basak (2013) opines that this type of analytics comes into play when predictive analytics is done. It focuses on the prescription of actions that are needed to be implemented for the predicted future events. "How can we make it happen?" is the question that is being tried to be answered by this type of analytics. This analytic utilises advance technologies and tools which makes it sophisticated to manage and implement. Ruohonem (2015) stated that the main characteristics of prescriptive analytics are; emphasis on decision alternatives and also the optimisation which is depending on future outcomes that were predicted, description of futuristic decision options and their impact on the business and visualisation format; scorecards and dashboards of future actions to be undergone based on the alternatives of decision and also the impact of the business.

Organisational Efficiency

Efficiency is a key growth driver because it enables managers to derive more output for a given input (Essien & Bello, 2016). Firm efficiency is generally understood as "a firm's ability to transform inputs into outputs" (Pham, 2014). Farrel (1957) says efficiency of a firm consists of two components, namely, technical efficiency and allocative efficiency (Primanthi, 2015). He further maintains that technical efficiency is "the ability of a firm to produce an optimal output from a given set of physical inputs (such as labour and equipment). While the allocative efficiency are "the inputs to be chosen at optimal prices and proportion to minimize the production cost when an organization has already been considered to be fully technically efficient" (Pham, 2014). Firm efficiency is often used interchangeably with productivity since the two terms describe the ability of a firm to transform its inputs into outputs (Dilling-Hansen, Madsen & Smith, 2003). Frijins, Margamtis, and Psillaki (2012) concluded that an efficiently operating firm is priced higher by investors than an inefficiently operating firm because an efficiently operating firm makes better use of its resources and is likely to have a lower default risk. For the purpose of this study technical efficiency was analysed towing the line of Pham's (2014) adoption of technical efficiency in his study on firm efficiency and stock return.

Firm efficiency is one of the most relevant constructs in the field of strategic management; a construct commonly used as the final dependent variable in various fields (Cho & Pucik, 2005; Richard, Derinney, Yip & Johnson 2009). It is believed that the essence of efficiency is the creation of value, therefore, value creation, as defined by the resource provider, is the essential overall efficiency criteria for any organization (Monday, Akinola, Ologbenla & Aladeraji, 2015). Continuous efficiency is the focus of any organization because only through efficiency are organisations able to grow and survive (Gavrea, Ilies & Stegerean, 2011). A business organization could measure its efficiency using the financial and non-financial measures.

Measures of Efficiency

Growth Rate

Growth rate refers to the rate at which variables in an organisation such as earnings has been or is expected to grow (FTE, 2008). Growth rate refers to the percentage change of a specified variable within a specific period with a stipulated context which acts as benchmarks. An organisations growth rate measures the percentage increase in the value of a variety of markets in which an organisation operates (Zack, 2009). An organisations growth rate can be achieved/improved on by boosting the organisations top line or revenue of the business with greater product sales or by increasing the bottom line or profitability of the operation by minimizing costs (Xesha, Iwu, Slabbert & Nduna, 2014). Growth rate refers to the percentage change of a specified variable within a specific period with a stipulated context which acts as benchmarks. Growth rate refers to the rate at which variables in an organisation such as earnings has been or is expected to grow (FTE, 2008). An organisations growth rate measures the percentage increase in the value of a variety of markets in which an organisation operates (Zack, 2009). An organisations growth rate can be achieved/improved on by boosting the organisations top line or revenue of the business with greater product sales or by increasing the bottom line or profitability of the operation by minimizing costs. Organisations are seen as living organisms and therefore, possess same characteristics with living organisms. In other words, organisations also have life cycle, they are formed (born), grow to maturity, decline, and finally die of age.

Every organisation strives to be relevant in its industry, therefore, this call for competition and excellent performance to be relevant in their choice of industry. Growth can be explained as the state of continuing to exist against all odds such as inconvenient situations, failures, or any ordeal. Falshaw, Glaister and Ekrem (2006) asserted that as organisation grows, workloads increase and in fact, strategies that were useful in the past seizes to be effective. Jones (2007) identified energy and resources (man and materials) as major contributory factors in organizational growth and hence determines its growth rate.

Innovation

Arancha, Carmen, Amaia, Pablo and Alrarez (2013) see innovation as the creation or development of new and more effective processes, services products, technologies, as well as the successful assimilation and exploitation of them. Innovation helps to improve economic growth, social development and business competitiveness. Many companies today, because of the competitive nature of the market are innovative, bringing about new ideas and modifying existing ones into their offerings. Innovation in businesses can be classified into; product market innovation and technological innovation (Lumpkin & Dess, 1996; Callaghan, McCusker, Lopez Losada, Harkin &

Wilson, 2009). Innovation represents a continuum ranging from willingness to try new innovations to a serious commitment to innovation. Firms that are highly innovative grow, however researches have reported that an innovative strategy is essentially speculative, with returns unknowable in advance, innovators run the risk of wasted resources if investment does not yield the hoped-for results. Innovations that become successful also risk imitation. However, alertness to and investment in new ways to create and capture value are key characteristics of businesses that pursue entrepreneurial strategy (Deakins & Freel, 2012).

Data Analytics and Organisational Efficiency

Data analytics plays a crucial role in identifying inefficiencies within organizations. Wang, Kung, and Byrd (2016) highlight that data analytics enables organizations to extract valuable insights from their vast amount of data, allowing them to identify areas of inefficiency and make data-driven decisions. Through the analysis of various data sources, such as customer feedback, sales figures, and operational data, organizations can gain a comprehensive understanding of their processes and identify bottlenecks or areas that require improvement. For example, by analyzing customer feedback data, organizations can pinpoint areas where customer satisfaction is low and take actions to rectify the underlying issues. Additionally, data analytics can help organizations identify patterns and trends that contribute to inefficiencies. By analyzing historical data, organizations can uncover recurring problems and devise strategies to address them more effectively. Furthermore, data analytics can assist in optimizing resource allocation by identifying areas where resources are underutilized or misallocated. By analyzing operational data, organizations can identify processes that are resource-intensive and streamline them to improve efficiency. Data analytics serves as a powerful tool for identifying inefficiencies within organizations, enabling them to make data-driven decisions and drive continuous improvement. (Wang *et al.,* 2016).

Data analytics has become an essential tool for organizations to enhance operational efficiency. According to Liu, Luo and Liu (2022), leveraging data analytics can help organizations identify patterns, trends, and insights from vast amounts of data, which in turn can inform decision-making and improve operational processes. One key strategy for leveraging data analytics is through predictive modeling. By analyzing historical data, organizations can develop predictive models that estimate future outcomes and trends. This allows organizations to proactively identify potential issues and take preventive measures to mitigate risks. Additionally, data analytics can be used to optimize operational processes. By analyzing data on key performance indicators (KPIs), organizations can identify bottlenecks or inefficiencies in their operations and implement targeted improvements. For example, through data analytics, organizations can identify areas where resources are being underutilized or where there is excessive waste, leading to cost savings and improved efficiency. Moreover, data analytics can enable organizations to gain real-time insights into their operations, allowing for timely adjustments and proactive decision-making. By leveraging technologies such as Internet of Things (IoT) devices and real-time data streams, organizations can monitor and analyze operational data in real-time, enabling them to respond quickly to changes or anomalies. In conclusion, leveraging data analytics has the potential to significantly improve operational efficiency by enabling organizations to make informed decisions, optimize processes, and gain real-time insights. (Liu *et al.* 2022).

Successful implementation of data analytics for organizational efficiency can be observed in various case studies. For instance, Popovič et al. (2018) conducted a study that focused on the implementation of data analytics in the healthcare industry. The researchers found that by utilizing data analytics, hospitals were able to improve operational efficiency and enhance patient care. Through the analysis of large volumes of patient data, hospitals were able to identify trends, patterns, and potential risk factors, which in turn allowed them to make informed decisions regarding resource allocation and patient treatment plans. This not only resulted in cost savings but also contributed to better patient outcomes. Another case study highlighted by Popovič et al. (2018) focused on the implementation of data analytics in the retail industry. By analyzing customer data, such as purchase history and browsing behavior, retailers were able to personalize marketing campaigns and optimize inventory management. This led to increased customer satisfaction, higher sales, and reduced costs associated with excess inventory.

Fiocco (2017) in studying the use of analytics in HR practices in Epsilon, found that analytics were used to analyse pay structures of employees which was useful during negotiations with trade unions. The use of analytics also helped Epsilon to detect that most of their employees were exposed to high risks of eye damage accounting for 30% of the company's accidents and so decided to provide glasses for all employees to reduce the number of accidents and eye defects. The analytic tool has enabled them to consistently track and reduce health and safety related issues and accidents among their workers, the causes as well as policies to help prevent those accidents.

Methodology

The study adopted the cross-sectional survey in its investigation of the variables. Primary source of data was generated through self- administered questionnaire. The population of the study was 810 employees of the 20 public hospitals in Rivers State, from which a sample of 265 employees was determined using the Krejcie and Morgan (1970) table. The reliability of the instrument was achieved by the use of the Cronbach Alpha coefficient with all the items scoring above 0.70. Data generated were analyzed and presented using both descriptive and inferential statistical techniques. The hypotheses were tested using the Spearman Rank Order Correlation Coefficient. The tests were carried out at a 95% confidence interval and a 0.05 level of significance.

Data Analysis and Results

A total number of 265 copies of the questionnaire was administered to the respondents and 221 which represents approximately 83.40% were returned and found usable for the analysis. 44 copies which represent 16.60% of the copies administered were not returned and some were incompletely filled, hence judged as invalid and unusable for the analysis. The response rate was adequate for the research and this indicated that the analysis could be done using the above questionnaires

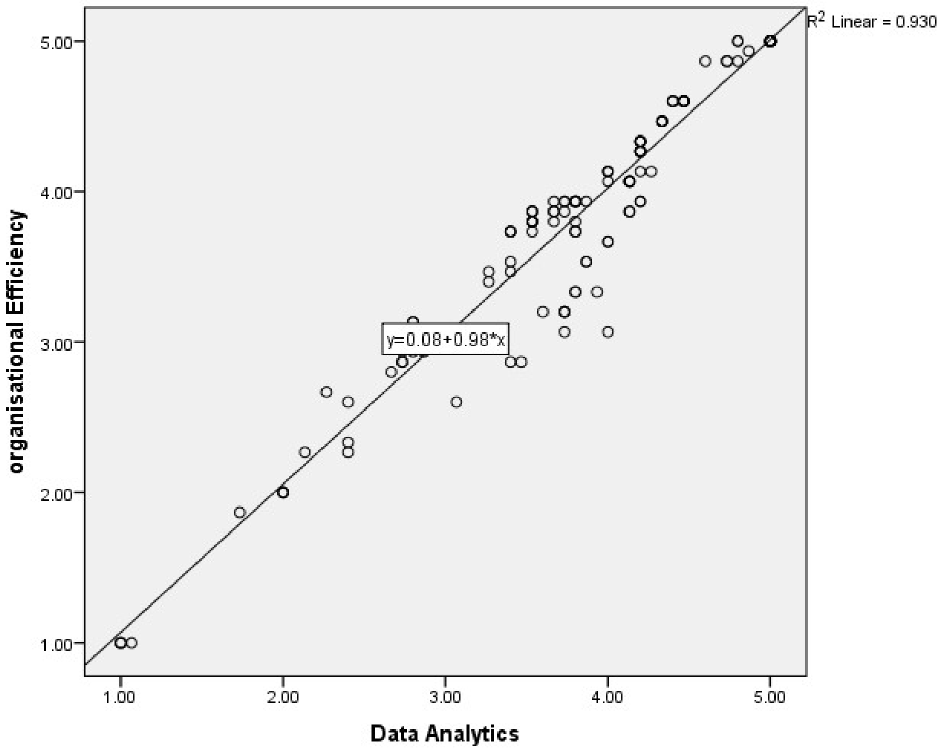


Figure 1: Scatter plot for data analytics and efficiency

Figure 1 shows a very strong relationship between data analytics (independent variable) and efficiency (dependent variable). The scatter plot graph shows that the linear value of (0.930) depicting a very strong viable and positive relationship between the two constructs. The implication is that an increase in data analytics simultaneously brings about an increase in the level of efficiency. The scatter diagram has provided vivid evaluation of the closeness of the relationship among the pairs of variables through the nature of their concentration.

Table 1: Correlation for descriptive Analytics and Efficiency measures

			Descriptive Analytics	Growth Rate	Innovation
Spearman's rho	Descriptive Analytics	Correlation Coefficient	1.000	.867**	.748**
		Sig. (2-tailed)	.	.000	.000
		N	138	138	138
	Growth Rate	Correlation Coefficient	.867**	1.000	.824**
		Sig. (2-tailed)	.000	.	.000
		N	138	138	138
	Innovation	Correlation Coefficient	.748**	.824**	1.000
		Sig. (2-tailed)	.000	.000	.
		N	138	138	138

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output

Ho1: There is no significant relationship between descriptive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Table 1 further shows a Spearman Rank Order Correlation Coefficient (rho) of 0.867 on the relationship between descriptive analytics and growth rate. This value implies that a very strong relationship exists between the variables. The direction of the relationship indicates that the correlation is positive; implying that an increase in growth rate was as a result of the descriptive analytics. Similarly displayed in the Table 1 is the statistical test of significance (p-value) which makes possible the generalization of our findings to the study population. From the result obtained the sig- calculated is less than significant level ($p = 0.000 < 0.05$). Therefore, based on this finding the null hypothesis earlier stated is hereby rejected and the alternate upheld. Thus, there is a significant relationship between descriptive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Ho2: There is no significant relationship between descriptive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Table 1 further shows a Spearman Rank Order Correlation Coefficient (rho) of 0.748 on the relationship between descriptive analytics and innovation. This value implies that a strong relationship exists between the variables. The direction of the relationship indicates that the correlation is positive; implying that an increase in innovation was as a result of the descriptive analytics. Similarly displayed in the Table 1 is the statistical test of significance (p-value) which makes possible the generalization of our findings to the study population. From the result obtained the sig- calculated is less than significant level ($p = 0.000 < 0.05$). Therefore, based on this finding the null hypothesis earlier stated is hereby rejected and the alternate upheld. Thus, there is a significant relationship between descriptive analytics and innovation of public hospitals in Rivers State, Nigeria.

Table 2: Correlation for descriptive Analytics and Efficiency measures

			Predictive Analytics	Growth Rate	Innovation
Spearman's rho	Predictive Analytics	Correlation Coefficient	1.000	.863**	.893**
		Sig. (2-tailed)	.	.000	.000
		N	138	138	138
	Growth Rate	Correlation Coefficient	.863**	1.000	.824**
		Sig. (2-tailed)	.000	.	.000
		N	138	138	138
	Innovation	Correlation Coefficient	.893**	.824**	1.000
		Sig. (2-tailed)	.000	.000	.
		N	138	138	138

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output

Ho3: There is no significant relationship between predictive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Table 2 further shows a Spearman Rank Order Correlation Coefficient (rho) of 0.863 on the relationship between predictive analytics and growth rate. This value implies that a very strong relationship exists between the variables. The direction of the relationship indicates that the correlation is positive; implying that an increase in growth rate was as a result of the predictive analytics. Similarly displayed in the Table 1 is the statistical test of significance (p-value) which makes possible the generalization of our findings to the study population. From the result obtained the sig- calculated is less than significant level ($p = 0.000 < 0.05$). Therefore, based on this finding the null hypothesis earlier stated is hereby rejected and the alternate upheld. Thus, there is a significant relationship between predictive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Ho4: There is no significant relationship between predictive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Table 2 further shows a Spearman Rank Order Correlation Coefficient (rho) of 0.893 on the relationship between predictive analytics and innovation. This value implies that a strong relationship exists between the variables. The direction of the relationship indicates that the correlation is positive; implying that an increase in innovation was as a result of the predictive analytics. Similarly displayed in the Table 1 is the statistical test of significance (p-value) which makes possible the generalization of our findings to the study population. From the result obtained the sig- calculated is less than significant level ($p = 0.000 < 0.05$). Therefore, based on this finding the null hypothesis earlier stated is hereby rejected and the alternate upheld. Thus, there is a significant relationship between predictive analytics and innovation of public hospitals in Rivers State, Nigeria.

Table 3: Correlation for Prescriptive Analytics and Efficiency measures

			Prescriptive Analytics	Growth Rate	Innovation
Spearman's rho	Prescriptive Analytics	Correlation Coefficient	1.000	.713**	.869**
		Sig. (2-tailed)	.	.000	.000
		N	138	138	138
	Growth Rate	Correlation Coefficient	.713**	1.000	.824**
		Sig. (2-tailed)	.000	.	.000
		N	138	138	138
	Innovation	Correlation Coefficient	.869**	.824**	1.000
		Sig. (2-tailed)	.000	.000	.
		N	138	138	138

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output

Ho5: There is no significant relationship between prescriptive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Table 3 further shows a Spearman Rank Order Correlation Coefficient (rho) of 0.713 on the relationship between prescriptive analytics and growth rate. This value implies that a strong relationship exists between the variables. The direction of the relationship indicates that the correlation is positive; implying that an increase in growth rate was as a result of the prescriptive analytics. Similarly displayed in the Table 1 is the statistical test of significance (p-value) which makes possible the generalization of our findings to the study population. From the result obtained the sig- calculated is less than significant level ($p = 0.000 < 0.05$). Therefore, based on this finding the null hypothesis earlier stated is hereby rejected and the alternate upheld. Thus, there is a significant relationship between prescriptive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Ho_6: There is no significant relationship between predictive analytics and efficiency of public hospitals in Rivers State, Nigeria.

Table 3 further shows a Spearman Rank Order Correlation Coefficient (rho) of 0.869 on the relationship between prescriptive analytics and innovation. This value implies that a very strong relationship exists between the variables. The direction of the relationship indicates that the correlation is positive; implying that an increase in innovation was as a result of the prescriptive analytics. Similarly displayed in the Table 1 is the statistical test of significance (p-value) which makes possible the generalization of our findings to the study population. From the result obtained the sig- calculated is less than significant level ($p = 0.000 < 0.05$). Therefore, based on this finding the null hypothesis earlier stated is hereby rejected and the alternate upheld. Thus, there is a significant relationship between prescriptive analytics and innovation of public hospitals in Rivers State, Nigeria.

Discussion of Findings

This study found that there is strong positive and significant relationship between data analytics and efficiency of public hospitals in Rivers State, Nigeria. This implied that data analytics is capable of transforming and enhancing the efficiency of public hospitals in Rivers State, Nigeria. This finding corroborates with Bersin (2013) who found that through the use of analytics, Maersk Drilling, an offshore drilling company as reported by Rasmussen and Ulrich (2015) decided to double the resource allocation towards their trainee program due to the strategic implications of the program as it increased their return on investment. Analytics was used as a change management process that helped to achieve those results for business impact. Also, Google through their People and Innovations Lab (PiLab) used analytics to identify four segments of managers and how their behaviour characteristics affected the organisation's management practices.

These findings corroborate with Ejo-Orusa and Okwakpam (2018) who carried out a study on predictive HR analytics and human resource management amongst human resource management practitioners in Port Harcourt, Nigeria and their finding revealed that there is a significant positive relationship between PHRA and the HRM practices used for the study. Based on the findings, it can be concluded that PHRA is an important factor in enhancing the HRM practice outcomes which subsequently increases sustainability of organizations.

These findings corroborate with Boudreau and Lawler III (2009) who averred the advent of analytics has increased the scope of making the HR function as a strategic partner This is as a result of the HR departments using prescriptive analytics being able to combine the humungous data on employees extracted to improve on the bottom line (Soumyasanto, 2016) and to achieve competitive advantage (Davenport, *et al.,* 2010) and enabled the HR function to add value to businesses (Boudreau, Lawler III & Levenson, 2004). The resultant effect has been increased organisational outcomes measured as customer, financial, learning and growth, and internal operations as established against short-term and long-term goals (Kaplan & Norton, 2007).

Conclusion and Recommendations

The study concludes that data analytics enhances the efficiency of public hospitals in Rivers State, Nigeria. This highlights the importance of leveraging data analytics to improve various aspects of healthcare delivery and enhance the overall efficiency of public hospitals. The findings reveal the potential benefits of data-driven approaches in healthcare management, emphasizing the importance of integrating data analytics into the operations of public hospitals to enhance efficiency and improve patient care outcomes.

Therefore, the study proffers the following recommendations:

i. Public hospitals should consider incorporating descriptive analytics practices into their operations. This involves collecting and analysing historical data on patient flow, resource allocation, operational processes, and healthcare outcomes.
ii. Public hospitals in Rivers State should consider implementing predictive analytics solutions to leverage the power of data in improving efficiency. These solutions can involve using historical data and advanced algorithms to forecast patient demand, anticipate disease outbreaks, optimize resource allocation, and enhance operational planning.
iii. Public hospitals in Rivers State should consider implementing prescriptive analytics solutions to optimize their operational efficiency. Prescriptive analytics goes beyond descriptive and predictive analytics by providing recommendations and actionable insights.

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