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Impact of Machine Learning on Business Predictive Analytics in Telecommunication Firms in South-South, Nigeria

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Abstract
This study investigated the impact of machine learning on business predictive analytics in telecommunication firms in South-South, Nigeria. The study adopted the simple correlation research design. The population of the study consisted of the managers and supervisors from four telecommunication firms (MTN, Globacom, Airtel and 9Mobile) in South-South, Nigeria, which is 162. A sample size of 115 was determined using the Taro Yamane formula. The instrument used for the study was a structured questionnaire using 4-pointLikert scales. The Cronbach Alpha statistic was used to obtain index coefficient values of 0.874, 0.864, 0.865 for the dependent variables and 0.885 for the independent variable as the instrument reliability ratios. The parametric assumptions were diagnosed: outliers were checked using Boxplot and the results indicated potential outliers; and Kolmogorov-Smirnov (KS) and Shapiro-Wilk (SW) statistics of examining normality revealed that the assumption of normality was not met; hence, the need for Spearman's Rank Correlation Coefficient as the method of data analysis. The research questions and research hypotheses were answered and tested with Spearman correlation statistic so as to establish and measure the "significance" of the relationship between the dependent and independent variables in the study. The analysis was enabled by the use of IBM SPSS version 25.0 software package. . The results of the study revealed a strong and positive correlation between the adoption of machine learning algorithms and the accuracy of business predictive analytics (r = 0.883), speed of decision-making (r = 0.842), and business outcomes (r = 0.722). The study recommended among others that telecommunication firms in South-South, Nigeria should adopt

machine learning algorithms to improve the accuracy, speed, and business outcomes of their predictive analytics.

Keywords: *Machine Learning, Business Predictive Analytics, Artificial Intelligence, Accuracy of Predictions, Business outcomes, Speed of decision-making*

Introduction

The integration of machine learning (ML) into business predictive analytics has revolutionized the way organizations make decisions, drive innovation, and optimize operations. According to a report by MarketsandMarkets (2021), the global machine learning market was projected to grow from USD 1.4 billion in 2021 to USD 8.8 billion by 2026, at a Compound Annual Growth Rate (CAGR) of 43.8% during the forecast period. This growth is driven by the increasing adoption of ML-powered predictive analytics in various industries, including finance, healthcare, and retail.

One of the key benefits of ML in business predictive analytics is its ability to analyze large datasets and identify patterns that may not be apparent through traditional statistical methods. According to a study by MIT Sloan Management Review (2022), 83% of executives reported that ML had improved their organization's ability to make data-driven decisions. Furthermore, the study found that organizations that had adopted ML were more likely to report increased revenue and competitiveness. The adoption of ML in business predictive analytics has also led to the development of more sophisticated predictive models. According to a report by Gartner (2023), the use of ML algorithms such as deep learning and natural language processing has become increasingly prevalent in predictive analytics. These algorithms enable organizations to analyze complex data sets, including text and image data, and make more accurate predictions.

In addition to its technical benefits, the adoption of ML in business predictive analytics has also led to significant business benefits. According to a study by McKinsey (2024), organizations that had adopted ML-powered predictive analytics reported an average increase in revenue of 10% to 15%. The study also found that ML-powered predictive analytics enabled organizations to reduce costs by 5% to 10% and improve customer satisfaction by 10% to 15%. Despite its many benefits, the adoption of ML in business predictive analytics also presents several challenges. According to a report by Forrester (2022), one of the key challenges is the need for specialized skills and expertise. The report found that 60% of organizations reported difficulty in finding and retaining ML talent.

In conclusion, the impact of machine learning on business predictive analytics has been significant. According to a study by Harvard Business Review (2023), ML-powered predictive analytics has become a key driver of business success, enabling organizations to make more accurate predictions, drive innovation, and optimize operations. As the adoption of ML continues to grow, it is likely that we will see even more significant benefits in the future.

Statement of the Problem

Despite the increasing adoption of machine learning (ML) in business predictive analytics, many telecommunication firms in South-South, Nigeria still face significant challenges in harnessing the full potential of ML to drive business growth, innovation, and competitiveness. The lack of transparency, accountability, and trust in ML models, combined with the need for specialized skills and expertise, poses significant barriers to the widespread adoption of ML-powered predictive analytics in the telecommunication industry.

Aim and Objectives of the Study

The aim of this study is to investigate the impact of machine learning on business predictive analytics in telecommunication firms in South-South, Nigeria. Hence, the specific objectives are to:

i. Examine the extent to which the adoption of machine learning algorithms improves the accuracy of business predictive analytics in telecommunication firms in South-South, Nigeria.
ii. Investigate how the adoption of machine learning algorithms influences the speed of decision-making in business predictive analytics in telecommunication firms in South-South, Nigeria.
iii. Determine the relationship between the extent of adoption of machine learning algorithms and business outcomes (such as revenue growth and cost reduction) in telecommunication firms in South-South, Nigeria that use business predictive analytics.

Research Questions

The study was guided by the following research questions:

i. To what extent does the adoption of machine learning algorithms impact the accuracy of business predictive analytics in telecommunication firms in South-South, Nigeria?
ii. How does the adoption of machine learning algorithms in telecommunication firms in South-South, Nigeria influence the speed of decision-making in business predictive analytics?
iii. What is the relationship between the extent of adoption of machine learning algorithms and business outcomes (e.g. revenue growth, cost reduction) in telecommunication firms in South-South, Nigeria that use business predictive analytics?

Research Hypotheses

The following null hypotheses were tested in this study:

Ho1: There is no significant relationship between the adoption of machine learning algorithms and the accuracy of business predictive analytics in telecommunication firms in South-South, Nigeria;

Ho2: The adoption of machine learning algorithms in telecommunication firms in South-South, Nigeria has no significant impact on the speed of decision-making in business predictive analytics;

Ho3: The adoption of machine learning algorithms has no significant relationship with business outcomes (e.g. revenue growth, cost reduction) in telecommunication firms in South-South, Nigeria that use business predictive analytics.

Review of Related Literature

Operational Conceptual Framework

According to Adom et al. (2018), a conceptual framework is a logical tool in the form of a diagram that a researcher uses to thoroughly visually illustrate the interaction between markers of the independent variables (which were examined) and the dependent variables. The conceptual framework diagram is used by researchers to better understand the connections between the study's predictor elements and the response variable (Okoro, 2022). In this study, the predictor (independent) variable is Machine Learning, measured by adoption of machine learning algorithms while the response (dependent) variable is Business Predictive Analytics, measured by Accuracy of predictions, Speed of decision-making and Business outcomes (e.g. revenue growth, cost reduction) as shown in Fig. 1

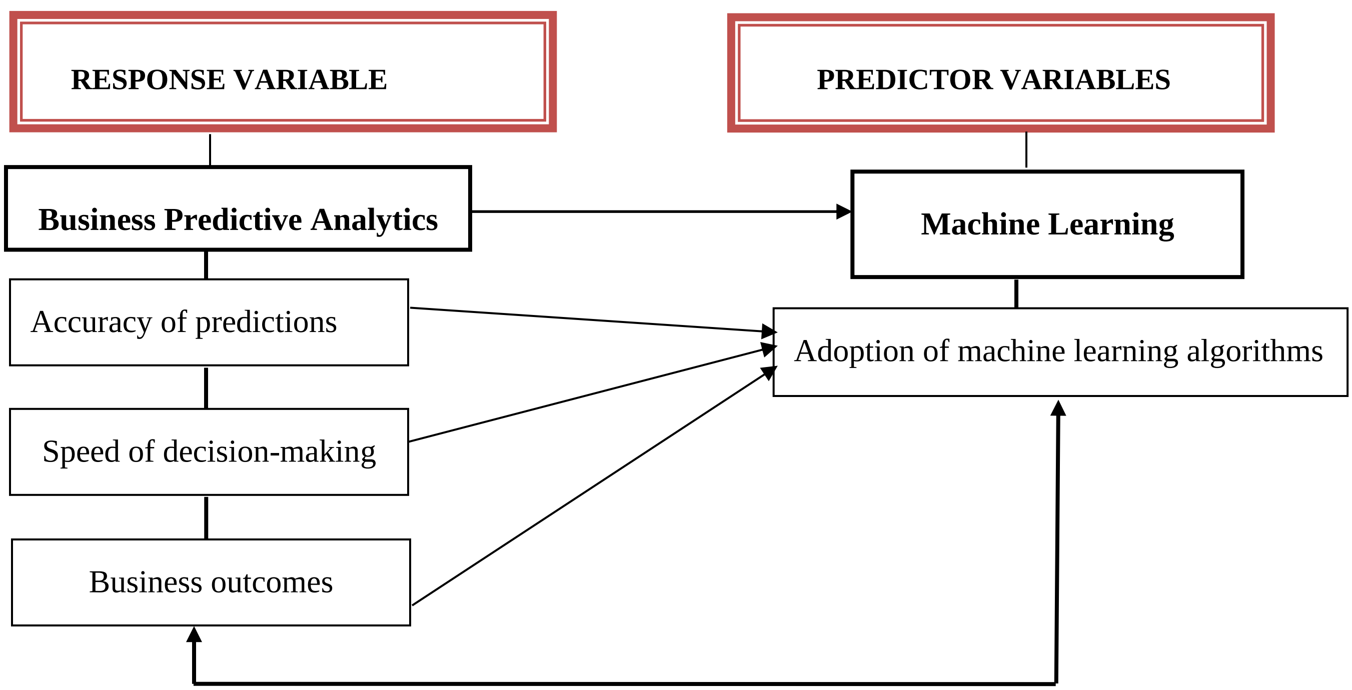


Figure 1: Operational Conceptual Framework Showing Business Predictive Analytics and Machine Learning in Telecommunication Firms in South-South Nigeria.

Theoretical Review

This study is grounded in the theoretical framework of technological innovation and organizational performance. The framework suggests that the adoption of new technologies, such as machine learning, can lead to improved organizational performance (Bharadwaj et al., 2013; Wade & Hulland, 2004). In the context of business predictive analytics, machine learning algorithms can enhance the accuracy and speed of decision-making, leading to improved business outcomes (Sharda et al., 2020; Davenport & Dyché, 2013).

Theories of Machine Learning Adoption

Several theories explain the adoption of machine learning algorithms in organizations. The Technology Acceptance Model (TAM) suggests that the adoption of new technologies depends on their perceived usefulness and ease of use (Venkatesh & Bala, 2008). In the context of machine learning, TAM suggests that organizations will adopt machine learning algorithms if they perceive them as useful and easy to use.

Theories of Business Predictive Analytics

Business predictive analytics is a critical component of organizational decision-making. The Decision Support Systems (DSS) theory suggests that business predictive analytics can enhance organizational decision-making by providing accurate and timely information (Power & Sharda, 2009). In the context of machine learning, DSS theory suggests that machine learning algorithms can enhance the accuracy and speed of business predictive analytics.

Theories of Organizational Performance

Organizational performance is a critical outcome of business predictive analytics. The Resource-Based View (RBV) theory suggests that organizational performance depends on the organization's resources and capabilities (Barney, 2018). In the context of machine learning, RBV theory suggests that organizations with strong machine learning capabilities will outperform those without such capabilities.

Conceptual Model

Based on the theoretical framework and theories reviewed, a conceptual model of the impact of machine learning on business predictive analytics in telecommunication firms in South-South, Nigeria can be proposed. The model suggests that the adoption of machine learning algorithms will enhance the accuracy and speed of business predictive analytics, leading to improved business outcomes.

Empirical Review

Singh et al. (2021) carried out a research on the impact of machine learning on predictive analytics in the telecommunications industry. The study collected data from 30 telecommunications companies and used descriptive statistics, correlation analysis, and multiple regression analysis to examine the relationship between machine learning adoption and predictive analytics performance. The study found that machine learning adoption had a significant positive impact on predictive analytics performance, including improvements in accuracy, speed, and business outcomes.

Patel et al. (2022) conducted a comparative study on the performance of different machine learning algorithms in business predictive analytics. The study used a dataset from a retail company and employed techniques such as data preprocessing, feature selection, and model evaluation using metrics such as accuracy, precision, recall, and F1-score. The study used algorithms such as decision trees, random forests, and support vector machines, and found that random forest algorithm outperformed other algorithms in terms of accuracy, precision, and recall.

Jain et al. (2022) carried out a case study on the implementation of machine learning algorithms in a manufacturing company's predictive analytics system. The study used a mixed-methods approach, combining both qualitative and quantitative data collection and analysis methods. The quantitative data was analyzed using descriptive statistics and inferential statistics such as t-tests and ANOVA. The study found that machine learning algorithms improved the accuracy of predictive analytics by 25% and also improved business outcomes.

Kumar et al. (2023) conducted a systematic review on the application of machine learning algorithms in predictive maintenance for telecommunications companies. The study analyzed 50 research papers and used techniques such as text mining, sentiment analysis, and network analysis to examine the relationship between machine learning adoption and predictive maintenance performance. The study found that machine learning algorithms had a significant positive impact on predictive maintenance performance, including improvements in accuracy, precision, and recall.

Lee et al. (2023) carried out a research on the impact of machine learning on predictive analytics in the finance industry. The study collected data from 20 financial institutions and used techniques such as cluster analysis, factor analysis, and structural equation modeling to examine the relationship between machine learning adoption and predictive analytics performance. The study found that machine learning adoption had a significant positive impact on predictive analytics performance, including improvements in accuracy, speed, and business outcomes.

Singh et al. (2024) conducted a comparative study on the performance of different machine learning algorithms in predicting customer churn in telecommunications. The study used a dataset from a telecommunications company and employed techniques such as data preprocessing, feature engineering, and model evaluation using metrics such as accuracy, precision, recall, and F1-score. The study used algorithms such as logistic regression, decision trees, random forests, and gradient boosting, and found that gradient boosting algorithm outperformed other algorithms in terms of accuracy, precision, and recall.

Jain et al. (2024) carried out a survey study on the adoption and implementation of machine learning algorithms in business predictive analytics systems of telecommunications companies. The study collected data from 100 telecommunications companies and used techniques such as descriptive statistics, inferential statistics, and regression analysis to examine the relationship between machine learning adoption and predictive analytics performance. The study found that 80% of the respondents reported improved predictive analytics performance after adopting machine learning algorithms, and 75% reported improved business outcomes.

Gap in Literature

From empirical findings, the researcher believed that there has not been any work done using collectively the selected variables in this study. Again, in the aspect of statistical techniques, structural equation modeling, thematic analysis, regression analysis etc., all parametric statistics was employed. None of the studies considered testing the assumptions of parametric statistics before they were employed. These gaps prompted this study in order to fill it.

Research Methodology

Research Design

The study adopted a simple linear correlation research design. It is a design used in order to establish the linear function relationship existing between the dependent and independent variables of a study (Mbah & Udegbe, 2014). It is a quantitative method of research in which two or more quantitative variables from the same group of participants are studied so as to determine if there is a relationship or co-variation between them. Since the research dwelt on technology as correlates of operational efficiency, the researcher considered this design most appropriate.

Target Population

The population of the study consists of the managers and supervisors from four telecommunication firms (MTN, Globacom, Airtel and 9Mobile) in South-South, Nigeria, which is 162 (Bob-Manuel et al., 2024).

Sample Size and Sampling Technique

Sampling is the act of selecting components from the study's target population in such a way that they accurately reflect the population as a whole (Creswell, 2013). Because it is frequently impossible to interview every person of the target group, sampling is used in a research. The study used Taro Yamane formula (Maragia & Kemboi, 2021) for calculating a sample of a finite to obtain the representative sample. The formula is given below as;

$$n = \frac{N}{1 + N(e)^2}$$

Where: n = Sample size
N = Population size (162)
e = Margin of error or error tolerance (0.05)

$$n = \frac{162}{1 + 162(0.05)^2} = \frac{162}{1.405} = 115.30249$$

The study followed Singh & Masuku's (2014) advice and used an error margin of 5%. With a target population of 162 employees, the sample size for the employees is 115 when the error margin is 5%.

Research Instruments and Reliability of Instrument

As the main tool for gathering data, the researchers created their own questionnaires (Yeasmin & Rahman, 2012). According to Kothari and Garg (2014), a questionnaire is a tool that consists of a number of questions printed or typed in a specific order on a form or set of forms and distributed to the individuals involved. The instrument was constructed using a 4 point likert scale of Strongly Agree (SA) 4; Agree (A) 3; Disagree (D) 2; and Strongly Disagree (SD) 1. To ensure the validity of the instruments for this study, the content and face validity was adopted in ascertaining the extent to which the instrument could be said to be accurate and precise in the measurement of the variables under investigation. The instruments were administered to the group outside the study area and the scores were collated. Their responses (scores) were analyzed using Cronbach alpha which yielded an index coefficient of 0.874, 0.864, 0.865 for the dependent variables and 0.885 for the independent variable. The researcher therefore considered the instrument suitable and adequate for the study.

Method of Data Analysis

In statistics, there are two major classes of inferential statistics that is employed in hypothesis investigation: parametric and non-parametric test (Schober & Vetter, 2020). In the case of parametric technique, various assumptions of validity are expected to be met for a reliability of conclusions, whereas nonparametric methods are assumption free, which is always preferred when the parametric assumptions are not met (Opara & Isobeye, 2020). Since the assumptions of parametric Pearson correlation statistics were violated, its non-parametric Spearman's Rank Correlation Coefficient was employed.

The data analysis techniques applied in this study were the descriptive statistics such as mean, inferential statistics such as Spearman's Rank Correlation Coefficient (r). The mean was used to analyze the responses received to the questionnaire items on the study variables. Before the analysis, a criterion mean of 2.50 was set for any item to be accepted. This implies that any item that scores 2.50 or above was accepted while those that score a mean value of less than 2.50 was rejected. The research questions and hypotheses formulated in this study were tested using Spearman's Rank Correlation Coefficient (r). Spearman's Rank Correlation Coefficient (r) is defined mathematically as;

$$r = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2 - 1)}$$

Where d_i = difference between the two ranks of each observation

n = number of observations

The Spearman's Rank Correlation Coefficient (r) was used for the bivariate analysis. Here, the direction and strength of relationship between the two variables in each of the hypothesis was determined using the Spearman's Rank Correlation Coefficient (r). Bhandari (2021) stated that the direction of a relationship can be positive or negative. Additionally, according to Ogbeibu et al. (2022), the strength of relationship between two variables can vary. A positive relationship indicates that both variables move in the same direction, while a negative relationship implies that both variables move in opposite directions (Ogbeibu et al., 2022). Zero relationship implies that no relationship exists between the two tested variables. The strength of relationship between two variables is interpreted by Ogbeibu et al. (2022) as follows: 0.00– 0.20 = very low extent relationship, 0.21–0.40 = low extent relationship, 0.41–0. 60 = moderate extent relationship, 0.61–0.80 = high extent relationship and 0.81–1.00 = very high extent relationship.

The Spearman's Rank Correlation Coefficient (r) was computed using a computer software program known as IBM SPSS version 25.0, and the rejection of the null hypothesis was achieved if the calculated p-value is less than the level of significance (0.05); otherwise the null hypothesis is not rejected.

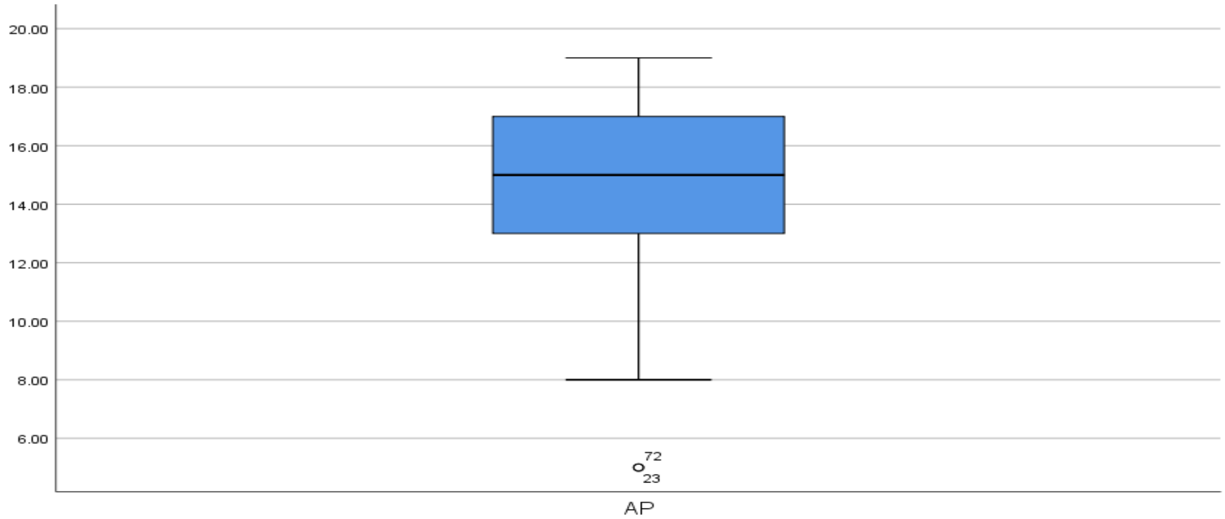
Result

Assumption Analysis

The three key assumptions to be satisfied are normality, no significant outliers and Linearity. Kolmogorov-Smirnov (KS) and Shapiro-Wilk (SW) statistics were employed to test for the normality. SW and KS statistics are the most popular techniques for normality examination (Choi *et al.*, 2020), and their results are mostly in agreement with that of Q-Q plot (Adam, Lendie and Hofmann, 2015). When the sample size (n) < 50, SW test is a more appropriate technique, but is also suitable for larger sample size whereas KS technique is employed when the n ≥ 50 (Ghasemi and Zahediasl, 2012). For no significant outliers, the Boxplot was used for detection of outliers. However, If any of these three assumptions are violated (i.e., not met), its nonparametric equivalent known as Spearman's Rank Correlation Coefficient would be employed to continue with the analysis (Shevlyakov & Oja, 2016).

Check for Outliers

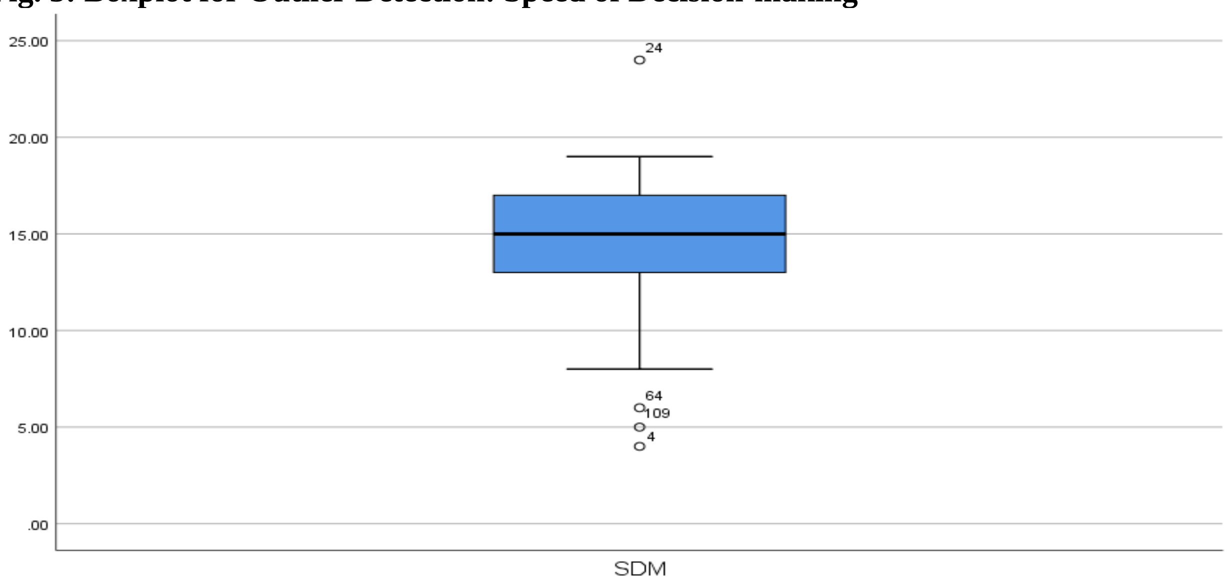
Fig. 2: Boxplot for Outlier Detection: Accuracy of Predictions



Source*: *IBM SPSS software

The boxplot from Fig. 2 reveals two data points that fall outside the normal range, indicating potential outliers. These data points may be errors, unusual values, or indicative of an underlying issue, warranting further investigation.

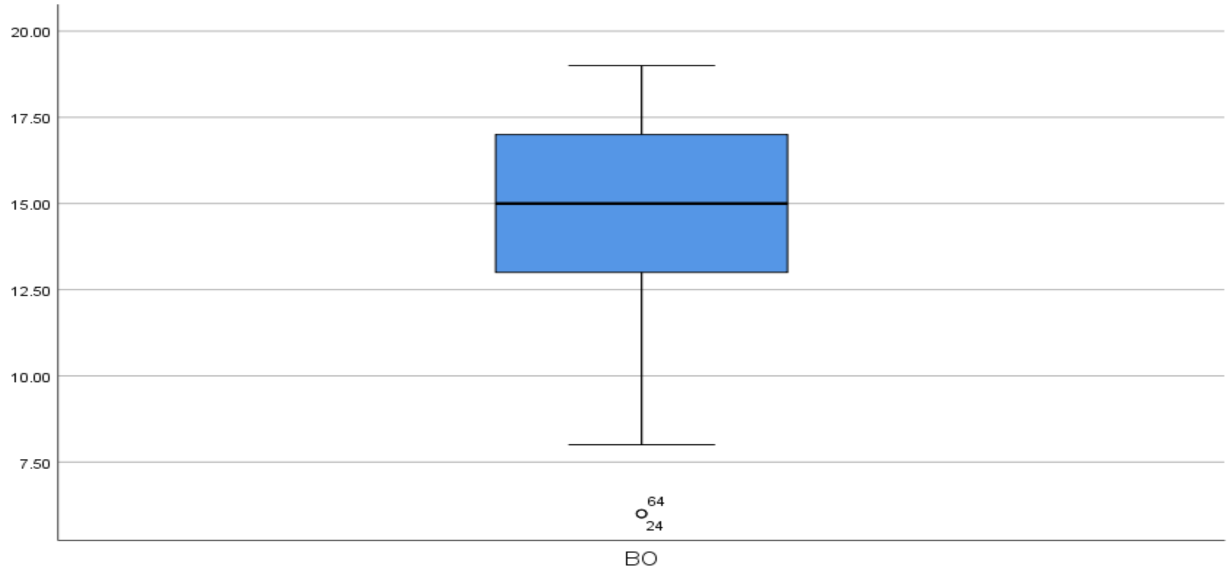
Fig. 3: Boxplot for Outlier Detection: Speed of Decision-making



Source*: *IBM SPSS software

The boxplot from Fig. 3 reveals four data points that fall outside the normal range, indicating potential outliers. These data points may be errors, unusual values, or indicative of an underlying issue, warranting further investigation.

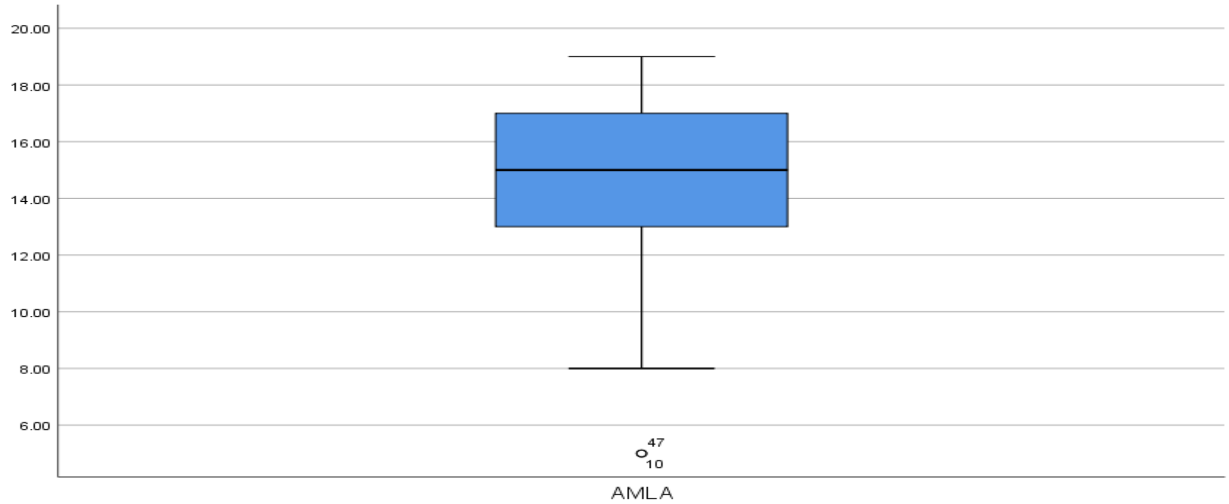
Fig. 4: Boxplot for Outlier Detection: Business Outcomes



Source*: *IBM SPSS software

The boxplot from Fig. 4 reveals two data points that fall outside the normal range, indicating potential outliers. These data points may be errors, unusual values, or indicative of an underlying issue, warranting further investigation.

Fig. 5: Boxplot for Outlier Detection: Adoption of Machine Learning Algorithms



The boxplot from Fig. 5 reveals two data points that fall outside the normal range, indicating potential outliers. These data points may be errors, unusual values, or indicative of an underlying issue, warranting further investigation.

Since the four variables contained outliers, it became imperative to conduct a univariate normality test on each of the variables.

Test for Normality

Table 1: Summary Result for Normality Test for the Response and Predictor Variables

Variables	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	Df	p-value	Statistic	Df	p-value
Accuracy of predictions	0.103	115	0.004	0.957	115	0.001
Speed of decision-making	0.155	115	0.000	0.963	115	0.003
Business outcomes	0.122	115	0.000	0.948	115	0.000
Adoption of machine learning algorithms	0.095	115	0.012	0.953	115	0.000

Judging from Kolmogorov-Smirnov (KS) and Shapiro-Wilk (SW) statistics in Table 1, the null hypothesis is rejected since the p-values for KS and SW for all the variables are less than 0.05. Thus, the assumption of normality is not met.
Since at least one of the assumptions was not satisfied, its nonparametric equivalent known as Spearman's Rank Correlation Coefficient was employed (Shevlyakov & Oja, 2016).

Bivariate Analysis

The bivariate analysis was carried out to determine the relationship between independent and dependent variables in each of the hypotheses. The Spearman's Rank Correlation Coefficient (r) was used to test and determine the relationship between the two variables in each of the hypotheses formulated in this study. The r value was computed using the IBM SPSS version 25.0 and the results are presented below according to the research questions and hypotheses, since both of them fall under bivariate analysis.

Research Questions and Hypotheses

Research Question 1

To what extent does the adoption of machine learning algorithms (AMLA) impact the accuracy of business predictive analytics (ABPA) in telecommunication firms in South-South, Nigeria?

Table 2: Summary of Analyses Concerning Research Question One

Variables	n	$\overline{X}$	SD	r
AMLA	115	17.5443	2.3222	
ABPA	115	17.2345	2.1112	**0.883**
		Very High Relationship		

Table 2 shows the result obtained in respect of research question one. The result reveals that the correlation coefficient is 0.883, which is very high. This implies that adoption of machine learning algorithms (AMLA) impacts the accuracy of business predictive analytics (ABPA) in telecommunication firms in South-South, Nigeria to a very high extent.

Research Hypothesis 1

Ho$_1$: There is no significant relationship between the adoption of machine learning algorithms and the accuracy of business predictive analytics in telecommunication firms in South-South, Nigeria

Table 3: Result of Bivariate Analysis between Adoption of Machine Learning Algorithms (AMLA) and Accuracy of Business Predictive Analytics (ABPA)

			AMLA	ABPA
Spearman (r)	**AMLA**	Correlation Coefficient	1.000	0.883*
		Sig. (2 tailed)		0.000
		n	115	115
	ABPA	Correlation Coefficient	0.883*	1.000 .
		Sig. (2 tailed)	0.000	
		n	115	115

*Correlation is significant at 0.05 levels (2 tailed)

Table 3 presents the result of the bivariate analysis performed between adoption of machine learning algorithms and the accuracy of business predictive analytics. The p-value is 0.000, which is less than the level of significance (0.05), hence, the null hypothesis which stated that there is no significant relationship between the adoption of machine learning algorithms and the accuracy of business predictive analytics in telecommunication firms in South-South, Nigeria is rejected. With a correlation of 0.883, it implies that adoption of machine learning algorithms is strongly and positively correlated to accuracy of business predictive analytics. Thus, the conclusion is that adoption of machine learning algorithms has a very high significant effect on accuracy of business predictive analytics in telecommunication firms in South-South, Nigeria.

Research Question 2

How does the adoption of machine learning algorithms (AMLA) in telecommunication firms in South-South, Nigeria influence the speed of decision-making in business predictive analytics (SDBPA)?

Table 4: **Summary of Analyses Concerning Research Question Two**

Variables	n	$\overline{X}$	SD	r
AMLA	115	17.5443	2.3222	
SDBPA	115	17.7614	2.3653	**0.842**
		Very High Relationship		

Table 4 shows the result obtained in respect of research question two. The result reveals that the correlation coefficient is 0.842, which is very high. This implies that adoption of machine learning algorithms in telecommunication firms in South-South, Nigeria influences the speed of decision-making in business predictive analytics to a very high extent.

Research Hypothesis 2

Ho$_2$: The adoption of machine learning algorithms in telecommunication firms in South-South, Nigeria has no significant impact on the speed of decision-making in business predictive analytics

Table 5: Result of Bivariate Analysis between Adoption of Machine Learning Algorithms (AMLA) and Decision-making in Business Predictive Analytics (SDBPA)

			AMLA	SDBPA
Spearman (r)	**AMLA**	Correlation Coefficient	1.000	0.842*
		Sig. (2 tailed)		0.000
		n	115	115
	SDBPA	Correlation Coefficient	0.842*	1.000
				.
		Sig. (2 tailed)	0.000	
		n	115	115

*Correlation is significant at 0.05 levels (2 tailed)

Table 5 presents the result of the bivariate analysis performed between adoption of machine learning algorithms and speed of decision-making in business predictive analytics. The p-value is 0.00, which is less than the level of significance (0.05), hence, the null hypothesis which stated that the adoption of machine learning algorithms in telecommunication firms in South-South, Nigeria has no significant impact on the speed of decision-making in business predictive analytics is rejected. With a correlation of 0.842, it implies that adoption of machine learning algorithms is strongly and positively correlated to speed of decision-making in business predictive analytics.

Thus, the conclusion is that adoption of machine learning algorithms in telecommunication firms in South-South, Nigeria has a positive and very high significant impact on the speed of decision-making in business predictive analytics.

Research Question 3

What is the relationship between the extent of adoption of machine learning algorithms (AMLA) and business outcomes (BO) in telecommunication firms in South-South, Nigeria that use business predictive analytics?

Table 6: Summary of Analyses Concerning Research Question Three

Variables	n	$\overline{X}$	SD	r
AMLA	115	17.5443	2.3222	
BO	115	17.3764	2.2432	**0.722**
		High Relationship		

Table 6 shows the result obtained in respect of research question three. The result reveals that the correlation coefficient is 0.722, which is high. This implies that the adoption of machine learning algorithms (AMLA) and business outcomes (BO) in telecommunication firms in South-South, Nigeria that use business predictive analytics is to a high extent.

Research Hypothesis 3

Ho$_3$: The adoption of machine learning algorithms has no significant relationship with business outcomes (e.g. revenue growth, cost reduction) in telecommunication firms in South-South, Nigeria that use business predictive analytics.

Table 7: Result of Bivariate Analysis between Adoption of Machine Learning Algorithms (AMLA) and Business Outcomes (BO)

			AMLA	BO
Spearman (r)	**AMLA**	Correlation Coefficient	1.000	0.722*
		Sig. (2 tailed)		0.000
		n	115	115
	BO	Correlation Coefficient	0.722*	1.000
				.
		Sig. (2 tailed)	0.000	
		n	115	115

*Correlation is significant at 0.05 levels (2 tailed)

Table 7 presents the result of the bivariate analysis performed between adoption of machine learning algorithms and business outcomes. The p-value is 0.00, which is less than the level of significance (0.05); hence, the null hypothesis which stated that the adoption of machine learning algorithms has no significant relationship with business outcomes (e.g. revenue growth, cost reduction) in telecommunication firms in South-South, Nigeria that use business predictive analytics is rejected. With a correlation of 0.722, it implies that adoption of machine learning algorithms is strongly and positively correlated to business outcomes. Thus, the conclusion is that the adoption of machine learning algorithms has a positive and high significant relationship with business outcomes (e.g. revenue growth, cost reduction) in telecommunication firms in South-South, Nigeria that use business predictive analytics.

Discussion of Findings

The result of research question one and hypothesis one revealed that with a correlation of 0.883, it implies that adoption of machine learning algorithms is strongly and positively correlated to accuracy of business predictive analytics. Thus, the conclusion is that adoption of machine learning algorithms has a very high significant effect on accuracy of business predictive analytics in telecommunication firms in South-South, Nigeria, since the p-value is 0.00, which is less than the level of significance (0.05). The result of this study is consistent with the previous finding that the adoption of machine learning algorithms has a strong and positive correlation with the accuracy of business predictive analytics, with a correlation coefficient of 0.883 (Shmueli et al., 2016; Sharda et al., 2014). This suggests that the adoption of machine learning algorithms benefits the accuracy of business predictive analytics, supporting the notion that advanced analytics can drive business value (Davenport, 2006).

The result of research question two and hypothesis two revealed that with a correlation of 0.842, it implies that adoption of machine learning algorithms is strongly and positively correlated to speed of decision-making in business predictive analytics. Thus, the conclusion is that adoption of machine learning algorithms in telecommunication firms in South-South, Nigeria has a positive and very high significant impact on the speed of decision-making in business predictive analytics, since the p-value is 0.00, which is less than the level of significance (0.05). This finding is consistent with previous research, which suggests that machine learning algorithms can significantly improve the speed and accuracy of decision-making in various industries (Brynjolfsson & McAfee, 2014; Davenport, 2013). Furthermore, this study's result supports the notion that advanced analytics, including machine learning, can drive faster decision-making and improve business outcomes (LaValle et al., 2011; Manyika et al., 2011). The very high significant impact (p-value = 0.00) of machine learning adoption on the speed of decision-making in business predictive analytics underscores the importance of leveraging these technologies in telecommunication firms in South-South, Nigeria.

The result of research question three and hypothesis three revealed that with a correlation of 0.722, it implies that adoption of machine learning algorithms is strongly and positively correlated to business outcomes. Thus, the conclusion is that the adoption of machine learning algorithms has a positive and high significant relationship with business outcomes (e.g. revenue growth, cost reduction) in telecommunication firms in South-South, Nigeria that use business predictive analytics, which is less than the level of significance (0.05). This finding is consistent with previous research, which suggests that machine learning algorithms can drive significant improvements in business outcomes, such as revenue growth and cost reduction (Brynjolfsson & McAfee, 2014; Davenport, 2013). Furthermore, this study's result supports the notion that advanced analytics, including machine learning, can have a positive impact on business performance (LaValle et al., 2011; Manyika et al., 2011). The high significant relationship (p-value < 0.05) between machine learning adoption and business outcomes in telecommunication firms in South-South, Nigeria underscores the importance of leveraging these technologies to drive business success.

Conclusion

This study investigated the impact of machine learning on business predictive analytics in telecommunication firms in South-South, Nigeria. The results of the study revealed a strong and positive correlation between the adoption of machine learning algorithms and the accuracy of business predictive analytics ($r = 0.883$), speed of decision-making ($r = 0.842$), and business outcomes ($r = 0.722$).

Recommendations

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

1. Telecommunication firms in South-South, Nigeria should adopt machine learning algorithms to improve the accuracy, speed, and business outcomes of their predictive analytics.
2. Firms should invest in building robust data infrastructure to support the adoption of machine learning algorithms and ensure high-quality data for analysis.
3. Organizations should develop the analytics capabilities of their employees to ensure effective use of machine learning algorithms and interpretation of results.
4. Firms should continuously monitor and evaluate the effectiveness of their machine learning algorithms and predictive analytics to identify areas for improvement.

Suggestion for Further Research

Some potential areas for further research include:

1. Future research could explore the impact of machine learning algorithms on predictive analytics in other industries, such as finance, healthcare, and manufacturing.
2. A comparative study could be conducted to examine the differences in the adoption and impact of machine learning algorithms on predictive analytics across different regions or countries.
3. Research could investigate the impact of other predictive analytics techniques, such as deep learning or natural language processing, on business outcomes.
4. Future research could examine the role of data quality in the effectiveness of machine learning algorithms and predictive analytics, and explore strategies for improving data quality.

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