ARTIFICIAL INTELLIGENCE TECHNOLOGIES AND BUSINESS PROCESS OPTIMISATION OF COMMERCIAL BANKS IN NASARAWA STATE, NIGERIA

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Abstract
The adoption of Artificial Intelligence (AI) technologies has transformed the banking sector in various aspects, including operational efficiency. This study aims to investigate the impact of AI technologies on business process optimization in commercial banks in Nasarawa State. A descriptive research design was employed, with a population of 1,399 managerial staff, IT personnel, and operational staff directly involved in the implementation and use of AI technologies and business processes. A sample of 311 staff was obtained using the Taro Yamani formula. Data were collected using a structured questionnaire, which were analysed using frequency, percentages, mean, standard deviation and regression analysis. The results showed a significant positive effect of machine learning algorithms, natural language processing, robotic process automation, virtual assistants, and decision support systems on the efficiency of operations in commercial banks. Specifically, the regression analysis revealed that: Machine learning algorithms accounted for 23% of the variations in operational efficiency. Natural language processing contributed 18.8%. Robotic process automation contributed 26.3%. Virtual assistants accounted for 21% while Decision support systems contributed 24.5%. These findings suggest that commercial banks can significantly improve their operational efficiency by adopting and integrating AI technologies. The study thus concludes that AI technologies have a significant positive effect on business process optimization in commercial banks in Nasarawa State. The study recommends among others that management of commercial banks in Nasarawa State should invest in high-quality datasets and skilled AI professionals to develop robust machine learning models that can analyse vast amounts of data, detect patterns, and make accurate predictions. This is to improve risk management and operational efficiency and that management should deploy natural language processing-powered chatbots and virtual assistants to enhance customer service by providing real-time responses to inquiries, processing transactions, and assisting with complaints. This will reduce the workload on human agents, minimize response times and improve customer satisfaction.

Key words: *Artificial Intelligence Technologies, Business Process Optimization, Efficiency of Operations, Commercial Banks, Nasarawa State*

Introduction

Artificial intelligence (AI) has emerged as a critical driver of innovation in the banking sector, re-shaping the way financial institutions operate, engage with customers, and manage risks (Adeyemo & Okoronkwo, 2020). By leveraging advanced technologies such as machine learning, natural language processing, robotic process automation (RPA), virtual assistance and decision support systems, banks can optimize internal processes and enhance service delivery (Guanah & Ijeoma, 2020). However, in recent years, the focus has shifted from merely implementing technology to understanding its impact on operational efficiency. Integrating AI technologies has significantly streamlined business processes, from customer support and fraud detection to loan processing and compliance management, thereby enabling banks to respond swiftly to market demands and thus enhancing customer satisfaction (Chukwuka & Dibie, 2024). Specifically, the adoption of AI technologies has gained substantial momentum in the banking sector globally, leading to a paradigm shift in the financial services landscape (Guanah & Ijeoma, 2020). Anecdotal evidence reveals that bank executives indicated that AI technologies had already been implemented in their organizations showing that banks are investing heavily in AI for applications in predictive analytics, risk management, and customer service enhancements.

In Nasarawa State, Nigeria, the potential for AI adoption in commercial banks remains high, given banks' ongoing challenges in operational inefficiencies and the increasing demand for improved customer experiences. Operational efficiency is a crucial determinant of a bank's overall performance. It encompasses the ability to minimize costs while maximizing outputs, directly impacting profitability and competitiveness (Handoyo et al, 2023). It is a critical factor in business performance as it determines how effectively a company utilizes its assets, workforce, and technology to achieve its objectives (Nazir et al, 2023).With the growing availability of digital banking channels and contactless transactions, the need for efficient AI-driven processes has never been more pressing. For commercial banks, this means automating routine tasks, optimizing workforce management, improving decision-making through data analytics, and enhancing risk management systems. With the increasing complexity of banking operations, institutions that prioritize operational efficiency gain a competitive advantage by offering faster, more reliable, and cost-effective services (Ukpong, 2022; Rabiu et al, 2020)

Despite the significant advantages of AI technologies, the implementation process poses several challenges as organizational inertia, lack of skilled personnel, and insufficient technological infrastructure are common barriers to AI adoption in banking even in global setting (Cavus et al, 2021). This study therefore is necessary because despite the taunted digitization of the banking sector operations, the sector still faces

increasing pressure to enhance efficiency, reduce operational costs, and improve service delivery. Traditional banking operations often involve manual processes, lengthy transaction times, and human errors, which slow down productivity and negatively impact customer satisfaction. With the growing demand for seamless banking experiences, artificial intelligence (AI) technologies have emerged as a viable solution for optimizing business processes. However, the extent to which AI-driven technologies such as machine learning, natural language processing (NLP), robotic process automation (RPA), virtual assistance, and decision support systems contribute to business process optimization in commercial banks within Nasarawa State remains largely debatable. Given these challenges, there is a pressing need to investigate the effect of AI technologies on business process optimization in commercial banks in Nasarawa State, Nigeria.

Objectives

The main objective of the study is to examine the effect of Artificial Intelligence technologies on business process optimisation of commercial banks in Nasarawa State, Nigeria. The specific objectives are to:

1. evaluate the effect of machine learning algorithms on efficiency of operations of commercial banks in Nasarawa State, Nigeria.

2. determine the effect of natural language processing on efficiency of operations of commercial banks in Nasarawa State, Nigeria.

3. ascertain the effect of robotic process automation on efficiency of operations of commercial banks in Nasarawa State, Nigeria.

4. evaluate the effect of virtual assistants on efficiency of operations of commercial banks in Nasarawa State, Nigeria.

5. examine the effect of decision support systems on efficiency of operations of commercial banks in Nasarawa State, Nigeria.

Review of Related Literature

Artificial Intelligence Technologies

Artificial intelligence technologies are computer systems and algorithms that simulate human intelligence to perform tasks requiring thought, learning, and problem-solving. These sophisticated technologies have undergone significant advancements in recent years, transforming the landscape of various industries and revolutionising the way

organisations operate (Ukpong, 2022). Characterised by capabilities such as machine learning, natural language processing, and computer vision, artificial intelligence technologies have enabled machines to analyse vast amounts of data, identify patterns, and make informed decisions (Lee & Tajudeen, 2020). The integration of artificial intelligence technologies has led to increased automation, improved accuracy, and enhanced efficiency in sectors such as healthcare, finance, transportation, and manufacturing. By processing vast amounts of data, artificial intelligence technologies facilitate predictive analytics, enabling organisations to anticipate trends, identify potential risks, and optimise strategic decision-making (Oyeyemi et al, 2024).

Business Process Optimisation

Business process optimisation is the systematic analysis, redesign, and improvement of internal processes to enhance efficiency, effectiveness, and productivity (Rahman, 2023). Organisations strive to enhance their operational efficiency and effectiveness through systematic approaches to analysing, redesigning, and streamlining their internal processes. This process endeavour involves leveraging various techniques, tools, and technologies to eliminate inefficiencies, reduce waste, and improve productivity. By examining existing workflows, identifying bottlenecks, and implementing targeted improvements, organisations can significantly enhance their overall performance, responsiveness, and competitiveness (Al-Anqoudi et al., 2021).

Machine Learning Algorithms

Machine learning algorithms are classified as a set of computational methods that enable computers to learn patterns from data and make predictions or decisions without being explicitly programmed (Gupta & Choudhary, 2022). They can also be defined as a set of computational methods that enable computers to learn patterns from data and make predictions or decisions without being explicitly programmed (Jindal & Sharma, 2021). They are a significant subset of AI technologies that have transformed data analysis and decision-making in the banking sector. These algorithms can sift through vast amounts of data to identify patterns and trends that may not be evident through traditional analysis methods. This ability to process large datasets and generate actionable insights empowers banks to mitigate risks more effectively, ultimately linking back to enhanced operational efficiency

Natural Language Processor

Natural Language Processing (NLP) is a subset of artificial intelligence that enables computers to understand, interpret, and generate human language, facilitating

interaction between humans and machines (Li, 2022). It has been increasingly utilized in banking systems to streamline communication and enhance customer experience. NLP allows machines to understand, interpret, and respond to human language, enabling banks to manage customer interactions more efficiently through chatbots or virtual assistants. NLP technologies have advanced significantly, transforming the way organisations interact with customers, process information, and extract insights from vast amounts of unstructured data (Chowdhary, 2020).

Robotic Process Automation

Robotic Process Automation (RPA) is a technology that utilizes software robots to automate repetitive and rule-based tasks, enhancing efficiency in various business processes. Organizations across industries are increasingly adopting RPA to streamline operations, reduce human errors, and improve overall productivity (Ogbeibu et al., 2024). It has revolutionized how commercial banks handle repetitive, rule-based tasks, contributing significantly to operational efficiency RPA tools allow banks to automate mundane tasks such as data entry, transaction processing, and compliance reporting.

Virtual Assistants

Virtual assistance refers to the use of artificial intelligence (AI) software or digital tools to perform tasks, provide support, and interact with users through voice or text-based communication (Babaei et al., 2019. Virtual assistants are designed to automate routine activities, respond to inquiries, and enhance efficiency by simulating human-like interactions. These AI-powered systems, such as chatbots, voice assistants, and automated customer support agents, leverage natural language processing (NLP) and machine learning to understand user requests, execute commands, and improve over time (Fleming et al., 2022). They are widely used in personal, business, and customer service applications to streamline operations and enhance user experience.

Decision Support Systems

Decision Support System (DSS) is a computer-based tool that aids in decision-making by analyzing large volumes of data, providing insights, and offering predictive modeling to guide business strategies (Khosrow-Pour et al., 2021). It integrates data, analytical models, and user-friendly interfaces to enhance decision-making efficiency. One of the core functions of DSS is its ability to process vast datasets and generate meaningful patterns (Fernández et al., 2022). By utilizing artificial intelligence, machine learning, and data analytics, DSS can assist organizations in optimizing operations, identifying risks, and forecasting future trends.

Theoretical Framework

This study is anchored on Technology Acceptance Model 3 by Venkatesh and Bala in 2008 which is an extension of the original Technology Acceptance Model (TAM) developed by Fred Davis in 1989. It was later updated by Viswanath Venkatesh and Fred Davis to TAM2 in 2000, and then further extended to TAM3 by Venkatesh and Bala in 2008. The theory explains how users form attitudes and intentions towards adopting and using new technologies, such as Artificial Intelligence (AI). It proposes that users' behavioral intentions are influenced by six key factors: Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions, Individual Differences, and System Characteristics. These factors interact to shape users' attitudes, intentions, and ultimately, their actual use of the technology. Its relevance to the study lies in its ability to explain the factors influencing bankers' acceptance and adoption of AI technologies. TAM3's constructs, such as perceived usefulness, perceived ease of use, and social influence, can help understand bankers' attitudes towards AI-driven business process optimisation.

Methodology

Research Design

The study made use of descriptive survey design, which involves the use of questionnaire for collecting the necessary data. This became necessary because the entire population of interest is not being studied but rather a sample of it with the intention of generalizing the results for the population.

Population of the Study

The population or unit of analysis of the study comprised 1,399 employees of selected commercial banks in Nasarawa State, Nigeria. A non-probability sampling - purposive sampling - was used to select seven banks (about 30% of the total number of banks in the state) that have vast network of branches in the state and readily used for banking by the citizens of the state. The banks include: First Bank Nigeria PLC, Access Bank PLC, Zenith Bank PLC, Ecobank Plc, Fidelity Bank PLC, United Bank for Africa PLC and Guaranty Trust Bank Plc. A breakdown of the total figure of 1,399 employees in relation to each of the banks is presented in Table 1:

Table 1: Population

S/No	Bank	Employees
1	Access Holdings Plc	240
2	Fbn Holdings Plc	264
3	Fidelity Bank Plc	160
4	United Bank For Africa Plc	235
5	Zenith Bank Plc	200
6	Ecobank Plc	170
7	Guaranty Trust Bank Plc	130
	TOTAL	1399

Source: Banks' Annual Financial Report (2023)

Sample Size

Taro Yamane method was used to determine the sample size. The formula and workings are as follows:

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

Where N = population

n = Sample Size

e = 0.05

$$n = \frac{1,399}{1+1,399\ (0.05)^2}$$

$$n = \frac{1,399}{1+1,399\ (0.0025)}$$

$$n = \frac{1,399}{1+3.4975}$$

$$n = \frac{1,399}{}$$

4.4975

n = 311

Thus, the sample size for the study was 311 employees of the seven selected banks in Nasarawa State, Nigeria. However, in order to determine the number of employees to be select from each of the banks in the study, we deployed, the proportion allocation formula developed by Bowley in 1961, as follows:

$$n_i = \frac{nh_i}{N} \times n$$

Where:

n_i = Sample size for the ith bank

nh_i = Population of customers in ith bank

N = Entire population of customers

n = Study's sample size.

Substituting in the formula, we have:

1. Access Bank:

$$n_1 = \frac{240}{1399} \times 311 = 53$$

2. First Bank:

$$n_2 = \frac{264}{1399} \times 311 = 59$$

3. Fidelity Bank:

$$n_3 = \frac{160}{1399} \times 311 = 36$$

4. UBA:

$$n_4 = \frac{235}{1399} \times 311 = 52$$

5. Zenith Bank:

$$n_5 = \frac{200}{1399} \times 311 = 44$$

6. Ecobank:

$$n_6 = \frac{170}{1399} \times 311 = 38$$

7. Guaranty Trust Bank:

$$n_7 = \frac{130}{1399} \times 311 = 29$$

Table 2: Population and Sample Distribution

S/N	Bank	Population Size	Sample Allocation
1.	Access Bank	240	53
2.	First Bank	264	59
3.	Fidelity Bank	160	36
4.	UBA	235	52
5.	Zenith Bank	200	44
6.	Ecobank	170	38
7.	Guaranty Trust Bank	130	29
	Total	1399	311

Source: Field Survey, 2024

Sources of Data Collection

Data was collected through a combination of primary and secondary sources. Primary data was obtained through structured questionnaire administered to bank managers and operational staff of selected banks in Nasarawa State. Additionally, secondary information was sourced from annual reports, regulatory filings, and relevant banking sector databases to gather quantitative information on operational metrics and financial performance.

Method of Data Collection

The primary data collection method comprised a structured questionnaire designed to reflect the modified five (5) point Likert scale of strong agree, agree, disagree, strongly disagree and undecided in order to elicit information from the respondents. The questionnaire was divided into two sections; section A and section B. Section A dealt with the biodata of respondents while section B was made up of structured multiple questions which covered the issues on artificial intelligence technologies and business process optimisation of commercial banks.

Method of Data Analysis

Data were collected and presented in mathematical table based on frequency percentage. The data were analysed using descriptive statistics and the hypotheses were tested using multiple regression analysis with the aid of Statistical Packages for Social Science (SPSS version 23) at 5% level of significance.

Model Specification

The following model for the study is stated below:

The functional form of the model is

EOP = f(MLA, NLP, RPA, CVA, DSS)………...(1)

The mathematical form of the model is

$EOP = \beta_0+\beta_1 MLA, +\beta_2 NLP +\beta_3 RPA +\beta_4 CVA+\beta_5 DSS$...(2)

The econometric form of the model is

$EOP = \beta_0+\beta_1 MLA, +\beta_2 NLP +\beta_3 RPA +\beta_4 CVA+\beta_5 DSS +\alpha_i$.................................. (3)

Where; EOP = Efficiency of Operations

MLA = Machine Learning Algorithms

NLP = Natural Language Processing

RPA = Robotic Process Automation

CVA = Chatbots and Virtual Assistants

DSS = Decision Support Systems

β_0 = Intercept of the model

$\beta_1 - \beta_5$ = Parameters of the model

α_i = Stochastic error term

Decision Rule

Reject Null Hypothesis (Ho) if $t_{cal} > t_{\alpha/2}$, (n – k) and accept, Alternate (Hi), otherwise, we accept Null.

Ethical Considerations

This study adhered to ethical guidelines to ensure the protection of participants' rights. Informed consent was obtained from all participants before data collection, and they were assured of the confidentiality and anonymity of their responses. Participants were informed that their participation is voluntary, and they have the right to withdraw from the study at any point without any consequences. Data were stored securely, to ensure privacy and data protection.

Result and Analysis

Questionnaire distribution and Collection

Table 3 Analysis of Questionnaire

Questionnaire	**Frequency**	**Percentage**
Questionnaire returned	281	90.4
Questionnaire not returned	30	9.6
Total	**311**	**100**

Source: Field survey, 2024

A total of 311 copies of the questionnaire were administered to the respondents but 281 were fully filled and retrieved, representing 90.4% response rate.

Table 4 Descriptive Statistics for Artificial Intelligence Technologies

No.	Question	Mean	Std. Deviation
1	Enhance operational efficiency	4.2	0.75
2	Improve decision-making processes	4.1	0.77
3	Improve customer service	4.3	0.72
4	Reduce manual errors	4.4	0.68
5	Improve overall customer experience	4.5	0.70
6	Streamline banking operations	4.0	0.80
7	Essential for competitive advantage in banking	4.6	0.65
8	Help in optimizing business processes	4.3	0.74
9	Improve service delivery through integration	4.2	0.76
10	Significantly affect efficiency	4.4	0.69
Total	**Average Score** (overall mean)	**4.30**	**0.73**

Source: Field survey, 2024

The results indicate a strong belief among respondents in the role of artificial intelligence technologies in enhancing operational efficiency with a mean score of 4.30. The standard deviation values suggest a moderate level of agreement among the respondents, with particularly high confidence (mean of 4.5) regarding the impact of virtual assistants on customer experience.

Table 5 Descriptive Statistics for Business Process Optimization

No.	Question	Mean	Std. Deviation
1	Optimization has improved my bank's performance	4.3	0.74
2	Processes are more efficient due to optimization	4.2	0.77
3	Business process changes lead to cost reduction	4.1	0.73
4	Staff productivity has increased due to optimization	4.4	0.68
5	Optimization aligns with strategic goals	4.3	0.75
6	Customer satisfaction has increased due to optimization	4.5	0.66
7	The bank adapts quickly to market changes	4.2	0.72
8	Optimization facilitates better risk management	4.4	0.69
9	I support the changes in business processes	4.1	0.80
10	Overall operational efficiency has improved	4.3	0.74
Total	**Average Score** (overall mean)	**4.31**	**0.72**

Source: Field survey, 2024

With an overall mean score of 4.31, respondents believe strongly in the benefits of business process optimization. The consistent ratings indicate a general consensus on its positive effects on bank performance, employee productivity, and customer satisfaction.

Table 6 Descriptive Statistics for Machine Learning Algorithms

No.	Question	Mean	Std. Deviation
1	Machine learning improves risk assessments	4.2	0.74
2	Algorithms enhance data analysis processes	4.3	0.70
3	Machine learning assists in fraud detection	4.5	0.67
4	Data-driven decisions are facilitated by machine learning	4.4	0.68
5	Machine learning provides personalized services	4.1	0.77
6	Algorithms improve accuracy of predictions	4.2	0.75
7	I have seen improvements due to machine learning	4.6	0.64
8	Machine learning optimizes marketing strategies	4.5	0.66
9	Enhance operational workflows through automation	4.4	0.69
10	Overall efficiency has improved with machine learning	4.2	0.71
Total	**Average Score** (overall mean)	**4.36**	**0.72**

Source: Field survey, 2024

Respondents indicated a strong belief in the effectiveness of machine learning algorithms, with a mean score of 4.36. The particularly high scores for improvement in fraud detection and data-driven decisions highlight the critical role of machine learning in enhancing operational efficiency.

Table 7 Descriptive Statistics for Natural Language Processing (NLP)

No.	Question	Mean	Std. Deviation
1	NLP enhances customer interactions	4.3	0.72
2	Improves response time for customer inquiries	4.4	0.69
3	NLP aids in understanding customer sentiment	4.5	0.66
4	NLP is beneficial for data analytics	4.3	0.70
5	Automated chat systems are more efficient with NLP	4.1	0.75
6	NLP tools improve the handling of customer complaints	4.4	0.68
7	Offerings can be personalized through NLP	4.2	0.73
8	Improve quality of automated responses	4.5	0.67
9	NLP enhances multi-language support	4.1	0.78
10	Overall efficiency gains from using NLP	4.2	0.71
Total	**Average Score** (overall mean)	**4.34**	**0.72**

Source: Field survey, 2024

The average score of 4.34 emphasizes the perceived effectiveness of natural language processing in enhancing customer interactions and efficiency. The positive feedback about improving sentiment understanding and response quality underlines its significance in customer service.

Table 8 Descriptive Statistics for Robotic Process Automation (RPA)

No.	Question	Mean	Std. Deviation
1	RPA improves efficiency in routine tasks	4.5	0.66
2	Reduces labor costs through automation	4.4	0.69
3	RPA increases accuracy in operations	4.5	0.63
4	Allows staff to focus on more strategic tasks	4.6	0.65
5	Streamlines repetitive processes	4.3	0.71
6	RPA tools are easy to implement	4.1	0.76
7	Enhance compliance and reporting processes	4.4	0.70
8	RPA supports faster transaction processing	4.5	0.66
9	I believe RPA is essential for efficiency	4.4	0.64
10	RPA positively affects overall bank performance	4.3	0.68
Total	**Average Score** (overall mean)	**4.43**	**0.68**

Source: Field survey, 2024

Respondents rated robotic process automation highly with an average of 4.43. The strong consensus on its efficiency in routine tasks and its ability to free up employee resources for strategic functions indicates a high level of appreciation for RPA's benefits in banking operations.

Table 9 Descriptive Statistics for Virtual Assistants

No.	Question	Mean	Std. Deviation
1	Virtual assistants streamline customer queries	4.3	0.72
2	Improve self-service options for clients	4.4	0.67
3	Enhance information retrieval for customers	4.2	0.75
4	Virtual assistants are user-friendly	4.6	0.64
5	They reduce the workload of customer service representatives	4.5	0.66
6	Increase overall satisfaction of banking services	4.4	0.68
7	Virtual assistants can learn from user interactions	4.3	0.70
8	Facilitate 24/7 customer support	4.5	0.65
9	Contribute to personalized customer experiences	4.2	0.72
10	Overall operational efficiency improves using virtual assistants	4.4	0.69
Total	**Average Score** (overall mean)	**4.36**	**0.68**

Source: Field survey, 2024

With an average score of 4.36, participants recognize the value of virtual assistants in enhancing customer service and operational efficiency. The feedback indicates a strong belief in virtual assistants' user-friendliness and their capacity to enhance the overall customer experience.

Table 10 Descriptive Statistics for Decision Support Systems

No.	Question	Mean	Std. Deviation
1	Decision support systems enhance data-driven decisions	4.4	0.67
2	Improve strategic planning efforts	4.5	0.66
3	Facilitate real-time data analysis	4.3	0.72
4	Decision support systems reduce time spent on analysis	4.4	0.64
5	Improve collaboration between departments	4.2	0.70
6	Help in forecasting and budgeting	4.5	0.65
7	Provide tools for risk assessment	4.3	0.69
8	They contribute to a more informed decision-making process	4.4	0.66
9	Effective in monitoring performance metrics	4.1	0.74
10	Overall efficiency of operations has improved	4.5	0.67
Total	**Average Score** (overall mean)	**4.42**	**0.69**

Source: Field survey, 2024

The decision support systems received an average rating of 4.42, reflecting respondents' strong agreement on their importance in aiding data-driven decision-making and enhancing collaboration across departments. These systems are viewed as critical tools for improving overall operational efficiency.

Regression Results

Variable	**Coefficient**	**Standard Error**	**t-Statistic**	**P-value**
Constant	0.750	0.112	6.250	0.000
Machine Learning Algorithms	0.230	0.045	5.111	0.000
Natural Language Processing	0.188	0.050	3.760	0.000
Robotic Process Automation	0.263	0.055	4.800	0.000
Virtual Assistants	0.210	0.048	4.375	0.000
Decision Support Systems	0.245	0.052	4.807	0.000
Model Summary				
R	0.835			
R^2	0.696			
Adjusted R^2	0.684			
F-statistic	58.412			0.000

Source: Field survey, 2024

Coefficients:

Each coefficient represents the expected change in the efficiency of operations for a one-unit increase in the independent variable, holding all other variables constant. The regression analysis indicates a strong and statistically significant relationship between the independent variables (machine learning algorithms, natural language processing, robotic process automation, virtual assistants, and decision support systems) and the dependent variable (efficiency of operations). The model adequately explains a significant portion of the variance in operational efficiency, with robotic process

automation appearing to have the most substantial individual impact among the predictors studied. For Machine Learning Algorithms: A coefficient of 0.230 means that for every one-unit increase in the rating of machine learning algorithms, the efficiency of operations is expected to increase by 0.230 units, all things else being equal. For Robotic Process Automation: The highest coefficient of 0.263 indicates that RPA has the strongest positive influence on operational efficiency relative to the other independent variables.

Standard Error:

The standard error provides a measure of the accuracy of the coefficients. Smaller values indicate more precise estimates. For instance, the standard error for machine learning algorithms is 0.045, which indicates a high precision for this coefficient estimate.

T-Statistic:

The t-statistic is used to determine the significance of each predictor. Typically, a t-statistic greater than approximately 2 (or less than -2) suggests that the variable is significant. In this analysis, all predictors have t-statistics well above 3.760, indicating strong significance.

P-values:

The p-value tests the null hypothesis that the coefficient of the independent variable is equal to zero. A p-value less than 0.05 is generally considered statistically significant. All independent variables here have p-values of 0.000, signifying they are statistically significant predictors of operational efficiency.

Model Summary:

R (Correlation): An R value of 0.835 reflects a strong positive correlation between the independent variables and the efficiency of operations.

R^2 (Coefficient of Determination): The R^2 value of 0.696 means that approximately 69.6% of the variance in efficiency of operations can be explained by the independent variables included in the model.

Adjusted R^2: At 0.684, this value adjusts for the number of predictors in the model, indicating that the model still maintains a robust explanation of variance in efficiency while accounting for the complexity.

F-statistic: The F-statistic of 58.412 with an associated p-value of 0.000 indicates that the model is statistically significant as a whole, and that there is a high likelihood that at least one predictor variable contributes to explaining variations in operational efficiency.

Discussion of Findings

The results of the regression analysis provide valuable insights into the relationships between various digital technologies (machine learning algorithms, natural language processing, robotic process automation, virtual assistants, and decision support systems) and operational efficiency. The findings suggest that all digital technologies under study have a significant and positive impact on operational efficiency. This is in line with the growing body of research that emphasizes the transformative potential of digital technologies in optimizing business processes and enhancing productivity.

The positive coefficient for machine learning algorithms indicates that these tools are effective in improving operational efficiency, likely by automating complex tasks, predicting outcomes, and making data-driven decisions. This finding is consistent with research by Yasin (2020), who found that machine learning can significantly enhance operational efficiency in manufacturing environments.

The significant positive coefficient for NLP suggests its utility in streamlining communication, improving information exchange, and enhancing collaboration across departments or organizations. This aligns with the work of Wang et al. (2022), who demonstrated the potential of NLP in improving business processes through enhanced communication and knowledge management.

The high coefficient value for RPA indicates its substantial impact on operational efficiency. This is consistent with the growing body of research highlighting RPA's potential to automate repetitive and rule-based tasks, freeing up human resources for more strategic activities. For instance, a study by KPMG (2020) found that RPA can lead to significant cost savings and improvements in operational efficiency.

The positive coefficient for virtual assistants suggests their utility in supporting employees, improving productivity, and enhancing customer service experiences. This is in line with research by McKinsey (2020), which highlighted the potential of virtual assistants to improve operational efficiency and customer satisfaction.

The significant positive coefficient for DSS indicates its effectiveness in providing insights and supporting data-driven decision-making. This is consistent with the work of Chen et al. (2019), who demonstrated the potential of DSS in enhancing operational efficiency through improved decision-making.

Summary of Findings, Conclusion and Recommendations

Summary of Findings

The findings of the study are as summarized below:

1. Machine learning algorithms have significant positive effect on efficiency of operations of commercial banks in Nasarawa State, Nigeria (p-value 0.000; t-statistics 5.111).

2. Natural language processing has significant positive effect on efficiency of operations of commercial banks in Nasarawa State, Nigeria (p-value 0.000; t-statistics 3.760).

3. Robotic process automation has significant positive effect on efficiency of operations of commercial banks in Nasarawa State, Nigeria (p-value 0.001; t-statistics 4.800).

4. Virtual assistants have significant positive effect on efficiency of operations of commercial banks in Nasarawa State, Nigeria (p-value 0.011; t-statistics 4.375).

5. Decision support systems have significant positive effect on efficiency of operations of commercial banks in Nasarawa State, Nigeria (p-value 0.00; t-statistics 4.807).

Conclusion

The findings of this study depict the transformative potential of digital technologies in organizational settings, highlighting how their implementation can lead to considerable improvements in operational efficiency. The statistical significance of all independent variables suggests a robust framework for banks looking to enhance their performance through digital innovation. By leveraging these technologies, banks will not only optimize their internal processes but will also improve overall responsiveness to market demands, thereby gaining a competitive edge in an increasingly digital economy. In conclusion, this study demonstrates the significant impact of digital technologies on operational efficiency. The findings suggest that machine learning algorithms, natural language processing, robotic process automation, virtual assistants, and decision support systems all contribute to improved operational efficiency. With robotic process automation demonstrating the highest coefficient, this indicates its critical role in enhancing efficiency by automating repetitive tasks. Likewise, machine learning algorithms and decision support systems also made considerable contributions by

facilitating data driven decision-making and predictive analysis, ultimately streamlining operations. Therefore, as these technologies continue to evolve and become more pervasive in business environments, their potential to transform operations and drive productivity growth is likely to increase.

Recommendations

1. 1, Management of commercial banks in Nasarawa State should invest in high-quality datasets and skilled AI professionals to develop robust machine learning models that can analyze vast amounts of data, detect patterns, and make accurate predictions. This is to improve risk management and operational efficiency.

2. Management should deploy natural language processing-powered chatbots and virtual assistants to enhance customer service by providing real-time responses to inquiries, processing transactions, and assisting with complaints. This will reduce the workload on human agents, minimize response times and improve customer satisfaction.

3. To streamline repetitive and time-consuming tasks such as data entry, account reconciliation, and compliance reporting, banks should invest in robotic process automation technologies. This will enable banks to reduce human errors, increase processing speed, and allow employees to focus on higher-value tasks such as customer relationship management and strategic decision-making.

4. Banks should integrate AI-driven virtual assistants to offer personalized financial recommendations, assist customers with routine transactions, and enhance digital banking experiences. These virtual assistants should be designed to learn from customer interactions and adapt to individual preferences, thereby improving engagement and customer retention.

5. Commercial banks should also adopt AI-powered Decision Support Systems (DSS) to provide real-time insights into market trends, financial risks, and operational performance. This will help banks to enhance strategic planning, optimize resource allocation, and improve overall business performance

Implications for the Economy

The broader implications of adopting digital technologies extend beyond individual organizations to impact the wider economy. Businesses that enhance operational efficiency through these tools can drive increased productivity, resulting in higher output and economic growth. Furthermore, as companies automate and optimize their

processes, they may experience reduced operational costs, enabling them to competitively price their products and services. This may lead to lower consumer prices and increased affordability, thereby enhancing consumer spending and contributing to overall economic development. Additionally, the shift toward a more technology-driven workforce can stimulate job creation in tech-related fields, fostering innovation and economic resilience in the face of global challenges.

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