

Evaluating Predictive Financial Analysis Techniques, Impacts, and Challenges in Nigerian Banking Institutions

Abstract:

This study examined the techniques, impacts, and challenges of predictive financial analysis in Nigerian Banking Institutions. The Nigerian Banking Institutions is the life wire of the nation's economy. They play a vital and massive role in the nation's economic development and financial system. The role of these institutions remains a catalyst for a nation's growth and development. Despite the importance of predictive financial analysis in improving financial performance, accurately forecasting financial outcomes, mitigating the impact of financial crises, and making informed decisions, many Nigerian banks still need help to adopt and use this technique effectively. As a result, this study aims to examine the predictive financial analysis, evaluate the techniques, impact, and challenges, and recommend possible solutions that can help address the challenges faced by the banking sector.

Methodology:

The study adopted a descriptive survey research design. A simple random sampling technique was used to select 7 respondents representing five banks (Access Bank, Fidelity Bank, First Bank, Wema Bank, and Zenith Bank). A self-designed online questionnaire (SDOQ) was used for data collection. The data collected were analyzed using descriptive statistics (percentage).

Results:

Banks: 2 of the respondents, representing 28.6%, work at Access Bank; 1 of the respondents, representing 14.3%, works at Fidelity Bank; 2 of the respondents representing 28.6%, works at First Bank, 1 respondent representing 14.3%, works at Wema Bank and the remaining 1 representing 14.3% works at Zenith bank.

Role of Respondents: AHOP, Compliance Officer, Data Administrator, Data Analyst/Analytics, Relationship Manager and Team Lead.

Analysis techniques: 3 banks representing 42.9% rely on the time series analysis technique, 2 banks representing 28.6% rely on the Regression analysis technique and 2 banks representing 28.6% rely on the machine learning algorithms technique.

Satisfaction Level: 3 respondents representing 42.9% are very satisfied with current predictive analytics capabilities, while 4 respondents representing 57.1% are moderately satisfied with current predictive analytics capabilities.

Discussion:

The study's findings revealed that the primary challenges faced by banks in implementing predictive financial analysis techniques include data quality issues, regulatory constraints, lack of expertise, and integration with existing systems. Similarly, most banks rely on time series analysis to forecast future financial trends.

Conclusion and Recommendations:

Based on the findings in this study, it was concluded that the primary challenges faced by banks in implementing predictive financial analysis techniques include data quality issues, regulatory constraints, lack of expertise, integration with existing systems, and others. Similarly, most banks rely on the time series analysis technique to forecast future financial trends. The findings in this study also revealed that respondents perceive the impact of technological advancements to improve accuracy significantly. It was therefore recommended that a robust data management system practice be established to ensure the accuracy and consistency of data. Also, beyond time series analysis, banks should explore other predictive analytics techniques to enhance forecasting accuracy.

Keywords: *Predictive Financial analysis, Technological advancements, Nigeria Banks.*

1. Introduction

Banks are the key players in economic development through adequate financing of economic activities (Kumshe et al., 2024). The Nigerian Banking Institutions is the life wire of the nation's economy. They play a vital and massive role in the nation's economic development and financial system. Similarly, the banking system is crucial to the growth and development of the economy because it plays a significant role in providing credit to the economy's productive sector (Kayode et al., 2021). The role of these institutions remains a catalyst for a nation's growth and development.

Similarly, they play a significant role in society, occupying a critical position in promoting economic growth (Wanke et al., 2015). Any shock suffered by the banking sector has a higher chance of negatively impacting the economy; thus, their performance is critical in discharging this responsibility (Olayinka et al., 2020). In this sector, banks must forecast financial trends, make informed decisions, and manage risk. This is due to the recent and swift evolution of data processing technologies and advanced analytical methodologies. However, despite their crucial role, Nigerian banks still need help predicting financial performance (Fadun & Oye, 2020; Gwaison & Maimako, 2021).

Over the years, literature has revealed that banks relied on traditional analytical methods whose purpose mainly focused on static factors. According to Adeola and Evans (2017), these traditional techniques generally entail analyzing credit histories, financial accounts, and other previous data sources to forecast future performance. Nigerian banks frequently rely on informal evaluations of a borrower's reputation and credit history within the local community

rather than formal credit scoring systems, which are more developed in advanced economies (Ezeoha, 2011). When determining a bank's trustworthiness, Nigerian banks frequently depend primarily on financial statements and ratio studies (Ezeoha, 2011). These approaches' static character makes it common for them to miss dynamic and quickly shifting economic conditions (Adeola & Evans, 2017). "The traditional methods are often criticized for their inability to accommodate the dynamic nature of financial markets and the complex interplay of factors that influence financial analysis" (Boot et al., 2021; Wewege & Thomsett, 2020).

"Therefore, the advent of predictive analysis has addressed these limitations by introducing models capable of analyzing a broader spectrum of variables, offering a more nuanced and comprehensive view of analysis" (Bonini & Caivano, 2021). "The evolution of predictive analysis in the banking sector has been characterized by several key trends reshaping the landscape of financial analysis and decision-making processes in banks" (Addy et al., 2024; Farayola et al., 2024). Addy et al. (2024) say "this trend involves integrating predictive analytics across diverse banking operations". "Banks are extending predictive models beyond traditional risk assessment to include customer segmentation, fraud detection, and personalized product offerings" (Devan et al., 2023; Addy et al., 2024). "This integration trend is not just a response to the availability of big data but also a strategic move towards a more holistic approach to banking operations" (Addy et al., 2024).

Koorapati et al. (2022) highlighted "this integration, noting the pivotal role of big data technologies in enabling banks to process and analyze large volumes of data efficiently". Similarly, (Gai et al., 2018) emphasize "these technologies' transformative impact in enhancing banks' analytical capabilities. The transition from traditional statistical models to more sophisticated machine learning algorithms, such as neural networks and ensemble methods, marks a significant shift". Deka (2014) observed that "these advanced models offer enhanced accuracy and flexibility, particularly in handling the complexities of modern financial data". Similarly, (Wamba et al., 2017) discuss "how this democratization empowers employees at various levels to engage in data-driven decision-making, fostering an analytics-centric culture within banks".

"Furthermore, the increasing reliance on predictive analysis has brought ethical and regulatory considerations. Banks are responding by implementing robust governance frameworks to ensure ethical compliance and alignment with regulatory standards", as noted by (Edilia & Larasati, 2023). The banking sector's approach to predictive analysis is

characterized by a move towards advanced modeling techniques, broader application across operations, democratization of tools, and heightened ethical and regulatory awareness. As revealed by the review, these trends indicate an expanding role for predictive analysis in banking, shaping future strategies and decision-making processes.

Predictive banking analysis represents changes in how financial institutions make decisions, manage risks, and ensure prompt customer service. According to (Andriosopoulos et al., 2019), “predictive analysis in the banking sector is applied in various areas, including credit risk assessment, fraud detection, customer relationship management, and financial analysis. The critical aspect of predictive analysis lies in its ability to process vast amounts of data to reveal information and trends that take time to determine. This approach offers a more objective and quantifiable way for decision-making”. In the opinion of (Lera et al., 2019), “the significance of predictive analysis in banking institutions cannot be overstated, as it contributes directly to the profitability and stability of the sector by enhancing their ability to mitigate potential losses associated with financial risk”. “Banks also use these predictive models to analyse customer data and predict their needs and preferences” (Singh et al., 2024). This enables them to offer personalized products and services, improving customer satisfaction and loyalty.

“Moreover, predictive analytics could significantly affect operational efficiency” (Rahman, 2023). “By automating complex analytical processes, banks can reduce the time and resources required for tasks such as credit scoring, risk assessment, and marketing campaign management. This automation improves efficiency and reduces the likelihood of human error, leading to more accurate and reliable outcomes” (Shaheen & Elfakharany, 2018).

Despite its numerous advantages, predictive analysis in banking could have its challenges. One of the primary concerns could be data privacy and security. Additionally, there could be a challenge of integrating predictive analysis into existing banking systems and workflows, which often requires significant investment in technology and training. Sarraf (2023) illustrated “the real-world application of statistical and predictive analyses in formulating strategic plans for financial companies. This case study highlights the potential of onboarding big data platforms and advanced feature selection capacities to enhance decision-making processes. It provides a practical example of how financial companies can leverage predictive analytics to develop strategic plans informed by data-driven insights, improving their overall performance and competitiveness”.

Similarly, the study by (Olaniyi et al., 2023) underscores “the marked improvement organizations experience in their ability to anticipate future trends and mitigate risks effectively. This research reviewed various techniques and applications of predictive analysis, demonstrating how raw data can be transformed into actionable insights. The findings from this study are particularly relevant for banks looking to adopt predictive analysis as a strategic asset, enhancing their competitiveness and fostering innovation”. Furthermore, Firdaus (2023) comprehensively analyses “how Islamic banks in Indonesia implement prudential principles and risk management in their financial operations. The research is significant as it sheds light on the unique challenges Islamic banks face, which must adhere to Islamic principles while managing financial risks effectively. The study explores various aspects of risk management, including credit, liquidity, market, and operational risks, and how these are managed within the framework of Islamic banking. The findings reveal that Indonesian Islamic banks have developed robust risk management practices aligning with Islamic principles and modern financial risk management standards”.

This case study is particularly valuable for understanding the intersection of religious principles and predicting financial risk management, offering insights that could apply to other Islamic banking institutions globally. The reviewed study has focused on using predictive financial analysis. However, to the author's knowledge, most have yet to focus on techniques and challenges, especially in the Nigeria Banking Institutions. **For this reason, investigating the main factors that influence the market indicators of banking institutions is both timely and important for all market stakeholders (Batrancea & Fetita, 2023).** It is against this that the study is conducted.

1.1 Statement of the Problem

Despite the importance of the Banking Institutions in the nation’s economy, the banking sector has experienced significant financial challenges in recent years (Gololo, 2018). **In recent years, local and international banks have faced numerous challenges, such as capital base problems, insufficient liquidity, market instability, and political and other economic issues (Shima et al., 2022; Effiong & Enya, 2020).** These challenges include high levels of non-performing loans, inadequate risk management, and financial instability (Nwosu et al., 2020; Chukwunulu et al., 2019; Abubakar et al., 2018). **Using various relevant statistical tools to examine the effect of risk management on financial performance, Kumshe, Bamanga, and Salihu (2024) found that credit risk management, market risk management, and capital**

adequacy risk management have positive and significant effects on the financial performance of the banks throughout the study. Similarly, despite the importance of predictive financial analysis to improve financial performance, accurately forecast financial outcomes, mitigate the impact of financial crises, and make informed decisions, many Nigerian banks still struggle to adopt and use this technique effectively (Lottu et al., 2023). As a result, this study aims to examine the predictive financial analysis, evaluate the techniques, impact, and challenges, and recommend possible solutions that can help address the challenges faced by the banking sector.

1.2 Objectives of the Study

1. To assess the predictive analysis technique banks use for forecasting future financial trends and how frequently
2. To Identify the key factors influencing the accuracy of predictive financial models.
3. To explore the impact of technological advancements on predictive capabilities.
4. To examine the relationship between predictive financial analysis and decision-making processes within banks.
5. To analyse the challenges and opportunities of predictive financial analysis in banks.
6. To explore perceptions and attitudes towards predictive analytics in decision-making.

1.3 Research Questions

The following research question will guide this study:

1. What predictive analysis technique does banks use for forecasting future financial trends and how frequently?
2. What are the key factors influencing the accuracy of predictive financial models?
3. What is the impact of technological advancements on predictive capabilities?
4. What is the relationship between predictive financial analysis and decision-making processes within banks?
5. What are the challenges and opportunities of predictive financial analysis in banks.
6. What are the perceptions and attitudes towards predictive analytics in decision-making?

2. Literature Review

2.1 Predictive Analytics Techniques

Predictive analytics techniques are often defined as technologies and methods that allow organizations to detect orientations and patterns in data, develop models, and test many variables. Organizations could use this analysis to achieve their desired goals and increase profits. In support of this view, Hoda et al. (2016) defined *predictive analytics* as a prediction of the future by analyzing past performance and studying historical data to uncover the relationships and patterns in these data. (Prasadababu and Hanumanth, 2014) added that predictive analytics help organizations predict risk and tendency and attain better revenues by enhancing their key metrics and making strategic corrections, and this is by making accurate predictions from structured and unstructured information. Those predictions are made based on models and techniques.

According to (Mohsen & Sharmin, 2018), the process of predictive analysis can be grouped into five phases, which include the identification of the problem, the collection, and preparation of the data, the analysis of the data, the development of the model, the deployment, observation and control of the predictive model. Therefore, predictive models are created during predictive modeling to discover the patterns between dependent and explanatory variables and predict an outcome (Prasadababu & Hanumanth, 2014). Various algorithms and techniques used in the predictive analysis, as postulated by (Meryem et al., 2016), are as follows:

Classification: A decisive outcome is used to predict the value of a decisive variable (class or target) by constructing a model based on one or multiple decisive or numerical variables (attributes or predictors). An example of classification is identifying whether an image contains a specific type of object, such as a truck or a car, or a product of acceptable quality from a manufacturing line.

Clustering (unsupervised learning) involves assigning observations into clusters containing similar observations and data. This process helps discover unknown relationships in a dataset. Clustering is the process of dividing a dataset into groups such that the members of each group are as similar as possible to one another and different groups are as dissimilar as possible. An example of clustering is creating a set of consumer segments based on data about individual consumers, including demographics, preferences, and buyer behavior.

Association rules: to find important associations in the observations, which means association rules find all item sets that have support greater than the minimum support and then use the large item sets to generate the desired rules that have confidence greater than the minimum confidence. An example of an association rules application is market basket analysis, which is a modeling technique that can be described simply as a customer buying a specific set of items, he will more or less probably buy another set of items.

Furthermore, the association rule is a machine-learning approach for finding exciting relationships between variables in large databases. It is designated to identify strong rules discovered in databases using some measures of interestingness. An association rule is an expression $X \rightarrow Y$, where X and Y are sets of items. The intuitive meaning of such a rule is that transactions of the database that contain X tend to contain Y . Association rules applied for market basket analysis. An example of such a rule might be that 98% of customers who purchase tires and automobile accessories also have automotive carried out.

Regression: numerical outcome, predicting the target value (numerical variable) by constructing a model based on one or more predictors (numerical and categorical variables). On the other hand, regression helps predict continuous outputs. That means the answer to

your question is represented by a quantity that can be flexibly determined based on the model's inputs rather than being confined to a set of possible labels.

2.2 Impact of technological advancement on predictive capabilities

The revolution of technology has a profound impact on predictive capabilities because significant technological advancements have revolutionized it. These developments have expanded predictive analysis capabilities, making it a critical tool across various sectors, including finance. With the advent of big data, predictive analysis has been provided with a rich source of information. Coupled with the advent of machine learning algorithms, it has become possible to process and analyze vast datasets to uncover hidden patterns and insights. For instance, in an example cited by (Mishra et al., 2019), big data predictive analytics and radio frequency identification technology are being used in the pharmaceutical industry to enhance supply chain performance (Mishra et al., 2019). The impact of technological advancement on predictive capabilities allows for more accurate forecasting and efficient resource allocation, leading to improved operational efficiency.

Predictive analysis is being increasingly adopted in various fields, even in supply chain management, particularly among small and medium-sized enterprises (SMEs). In line with this, the study of (Sodero et al., 2022) has shown that technological factors such as relative advantage and compatibility play substantial roles in adopting predictive supply chain business analytics. This adoption is driven by the need to improve efficiency, reduce costs, and enhance decision-making processes. These technological advancements in predictive analysis have led to more accurate and timely maintenance interventions, enhancing system durability and operational efficiency (Gidiagba et al., 2024). Despite these advancements, predictive analysis faces challenges, particularly in data privacy, ethical considerations, and the need for financial cast.

2.3 Challenges of Predictive Analysis

As opined by (Leo et al., 2019), data quality and availability are one of the challenges of predictive analysis. The efficacy of predictive models usually depends on the quality and quantity of data. Most banks often need help with issues related to incomplete, inconsistent, or outdated data, which can prevent the accuracy of predictive analytics. This challenge remains persistent and, therefore, requires ongoing attention and research. Similarly, as highlighted by (Wamba et al., 2017), another prominent challenge is the need for more data scientists and analysts with the requisite expertise. Banks face the challenge of recruiting and retaining talent capable of developing, implementing, and interpreting predictive models.

Another notable challenge, as discussed by (Gelindon et al., 2022), is the interpretability of complex predictive models, particularly neural networks. While these models exhibit high accuracy, their inner workings can be inscrutable. Banks need to strike a balance between model accuracy and transparency, especially in contexts where regulatory authorities and stakeholders demand explainable decision-making processes. Additionally, the adoption of predictive analytics in banking necessitates a skilled workforce proficient in data science and analytics. The ethical considerations surrounding predictive analytics cannot be overlooked, as underscored by (Edilia & Larasati, 2023).

Furthermore, as observed by (Koorapati et al., 2022), the integration of big data technologies and AI-driven analytics is another challenge because it requires substantial investments in infrastructure and technology. Smaller banks may need more financial resources, potentially limiting their ability to leverage these advanced tools effectively. Moreover, there is a need

for continuous model monitoring and recalibration. Predictive models are not static; they require regular updates to remain effective in dynamic financial markets. Failure to monitor and recalibrate models can lead to inaccurate risk assessments, as pointed out by (Shakya & Smys, 2021).

Other technical and organizational challenges as highlighted by (Ventana, 2015) are as follows:

1. Difficulty of integrating predictive analytics into organization's information architecture;
2. Difficulty of accessing source data;
3. Difficulty of using the results;
4. Lack of resources including budget and skills;
5. Lack of awareness - an understanding of how to apply predictive analytics to business problems;
6. Lack of in-house experts to implement the results;
7. Focusing on past patterns;
8. The data is too expensive to measure;
9. Low accuracy of results

2.4 Benefits of predictive analysis

Using predictive analysis to support business core functions such as marketing, merchandising, sales, and risk management has numerous benefits. According to several recent studies, organizations that incorporate predictive analysis into their business can realize significant benefits. These benefits as stated by (Siegel, 2016; Stedman, 2017; Kalakota, 2014) include the following:

Optimize productivity and cost efficiency;

More rapid identification of emerging opportunities

Higher levels of profitability

Greater customer loyalty and retention

Faster detection and corrections of problems

Reduce risk, eliminate waste, and accelerate time to improvement

Determine true process capacity

Reduce process cycle time

Optimize resources especially staffing levels and schedules

Improve equipment maintenance and reliability

Real-time insights of equipment health and performance

Improve availability, reliability and decision-making and many other benefits.

3. Materials and Methodology

This study adopted a descriptive research design. This design allowed the researcher to present a series of inquiries to individuals who participated in the study and summarized their responses. This study's target population comprised all banks in Nigeria. The sample size included 7 individuals randomly selected from the bank's head offices as the branches do not have a data analytics department and could not provide experts to respond to the question. The respondents were from 5 banks: Access Bank, First Bank of Nigeria, Fidelity Bank, Wema Bank, and Zenith Bank. Therefore, the data is representative of the banks.

Data for the study were collected using a self-designed online questionnaire (<https://docs.google.com/forms/d/1Kvl3kw9lRqgCBmw7LdZsVr4JXicVFkWwQy9ulB8s0M>).

The questionnaire consisted of 10 questions, 8 of which contained options to choose from, while the remaining two were open-ended. The Data Collected was analyzed using descriptive statistics of frequency count (percentage).

4. Data Description and Analysis

4.1 Demographic Data:

4.1.1 In what capacity do you work in?

Table 1: Frequency Showing various capacity where respondents work.

Office	Frequency	Percentage
AHOP	1	14.3
Compliance Officer	1	14.3
Data Administrator	1	14.3
Data Analyst	1	14.3
Data Analytics	1	14.3
Relationship Manager	1	14.3
Team lead, non-financial transactions, First Bank	1	14.3

Total	7	100.0
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The data in Table 1 shows the different capacities where respondents work. Respondents work as AHOP, Compliance Officer, Data Administrator, Data Analyst/Analytics, Relationship Manager, and Team lead.

4.1.2 What is the name of your bank?

Table 2: Frequency showing the respondent's bank name

Banks	Frequency	Percentage
Access Bank	2	28.6
Fidelity Bank	1	14.3
First Bank	2	28.6
Wema Bank	1	14.3
Zenith Bank	1	14.3
Total	7	100.0

Data in Table 2 shows the name of the bank where the respondent works. 2 of the respondents, representing 28.6%, work at Access Bank, 1 of the respondents, representing 14.3%, works at Fidelity Bank, 2 of the respondents, representing 28.6%, work at First Bank, 1 respondent representing 14.3% works at Wema Bank while the remaining 1 representing 14.3% works at Zenith bank. Respondents who worked at Access Bank and First Bank were more numerous. This was based on availability and access to respondents.

4.2 Answering Research Questions

4.2.1 Research Question One: What predictive analysis technique does banks use for forecasting future financial trends and how frequently?

- a. **How frequently does your bank utilise predictive analysis for forecasting future financial trends?**

Table 3: Frequency of how frequently banks utilise predictive analysis for forecasting future financial trends

Bank	Frequency	Frequency	Percent
Zenith, Access and Wema	Daily	3	42.9
First Bank and Fidelity Bank	Monthly	2	28.6
Access Bank and First Bank	Occasionally	2	28.6
	Total	7	100.0

Table 3 data shows how frequently banks utilize predictive analysis for forecasting future trends. 3 banks, representing 42.9%, utilize predictive analysis daily, 2 banks, representing 28.6%, utilize predictive analysis monthly, while 2 banks, representing 28.6%, use predictive analysis occasionally. From this data, Zenith Bank and Wema Bank have been seen to use predictive analysis daily. This indicates the effectiveness of using predictive analysis for

forecasting future financial trends. However, Access Bank, from the data, revealed that they use predictive analysis Daily and Monthly. This might be due to the respondents' years of experience giving the information. Access banks might have moved from monthly to daily to enhance accuracy, while the respondents who gave the information might need to be made aware (due to promotion from the local branch to head office).

Similarly, First Bank uses predictive analysis monthly and occasionally. This indicated variations in analytical frequency within the bank, a weakness. Therefore, it can be said that most banks utilize Predictive analysis daily.

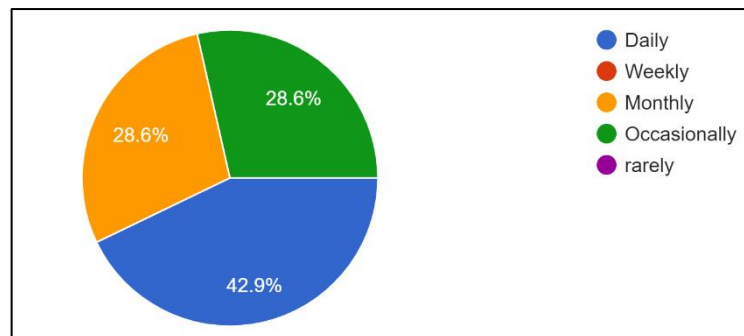


Fig 1: Chart showing how frequently bank utilizes predictive analysis for forecasting of future trends

b. Which predictive analysis techniques does your bank primarily rely on for forecasting future financial trends? (Select all that apply)

Table 4: Frequency of predictive analysis techniques bank primarily rely on for forecasting future financial trends.

Bank	Technique	Frequency	Percent
Access, First and Wema Bank	Time Series Analysis	3	42.9%
Zenith and Access	Regression Analysis	2	28.6%
First Bank and Fidelity Bank	Machine learning algorithms	2	28.6%
Total		7	100.0

Table 4 data shows predictive analysis techniques bank primarily rely on for forecasting future financial trends. 3 banks representing 42.9% rely on time series analysis technique, 2 banks representing 28.6% rely on Regression analysis technique while 2 banks representing 28.6% rely on machine learning algorithms technique. From the data, it was revealed that Access Bank rely on Time Series Analysis and Regression Analysis for forecasting future financial trends. First Bank rely on Time series analysis and Machine Learning algorithms. Fidelity Bank rely on Machine learning algorithms, Wema Bank rely on Time Series Analysis while Zenith bank rely on Regression. Access Bank and First Bank rely on two predictive

analysis technique while Fidelity, Wema and Zenith Bank rely on one predictive analysis technique for forecasting future financial trends. Therefore, it can be concluded that most banks rely on time series predictive analysis technique because of its accuracy in forecasting future financial trends.

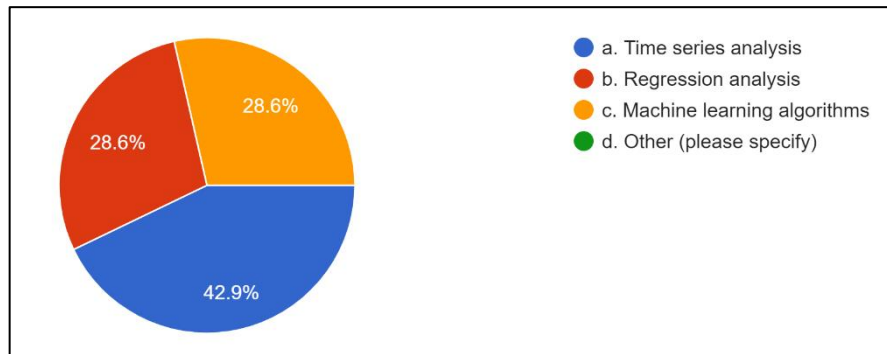


Fig 2: Chart showing predictive analysis techniques bank primarily rely on for forecasting future financial trends

4.2.2 Research Question Two: What are the key factors influencing the accuracy of predictive financial models?

c. In your opinion, what are the primary factors influencing the accuracy of predictive financial models used in your bank? (Select all that apply)

Table 5: Frequency on the primary factors influencing the accuracy of predictive financial models.

Banks	Factors	Frequency	Percentage
Zenith	Quality of input data, Model Complexity, Technological infrastructure, Expertise of analysts	1	14.3
First Bank and Fidelity Bank	Technological infrastructure	2	28.6
Access Bank and First Bank	Quality of input data, Model Complexity, Market volatility, Technological infrastructure, Expertise of analysts	2	28.6
Access Bank	Quality of input data, Model Complexity, Technological infrastructure, Others	1	14.3

Wema Bank	Quality of input data, Model Complexity, Market volatility	1	14.3
	Total	7	100.0

Table 5 data shows primary factors influencing the accuracy of predictive financial models. Factors influencing the accuracy of predictive financial model in Access bank include: Quality of input data, Model Complexity, Market volatility, Technological infrastructure, Expertise of Analysts and others. Factors influencing the accuracy of predictive financial model in Fidelity Bank include Technological infrastructure. Factors influencing the accuracy of predictive financial model in First bank include: Quality of input data, Model Complexity, Market volatility, Technological infrastructure, Expertise of analysts. Factors influencing the accuracy of predictive financial model in Wema bank include: Quality of input data, Model Complexity, Market volatility. Factors influencing the accuracy of predictive financial model in Zenith bank include: Quality of input data, Model Complexity, Technological infrastructure, Expertise of analysts. From the data in table 5, the common primary factors influencing the accuracy of predictive financial models in Banks are Quality of Input Data and Model Complexity. However, the only factor that influence the accuracy of predictive financial models in Fidelity Bank is Technological Infrastructure. Access bank and Zenith Bank has similar factors in terms of Expertise of analysts while Wema Bank and Access Bank are similar in market volatility. First Bank, Fidelity Bank, Access Bank and Zenith Bank are similar in technological infrastructure. First Bank, Fidelity Bank, Access Bank, Wema Bank and Zenith Bank have more than one factor influencing the accuracy of predictive financial models while Fidelity has only one factor which made it different.

4.2.3 Research Question Three: What is the impact of technological advancements on predictive capabilities?

- d. How do you perceive the impact of technological advancements, such as artificial intelligence and machine learning, on the predictive capabilities of financial analysis tools in your bank?

Table 6: Frequency on the impact of technological advancements on predictive capabilities.

	Frequency	Percentage
Significantly improves accuracy	5	71.4
Moderately improves accuracy	2	28.6
Total	7	100.0

Table 6 data shows the impact of technological advancements on predictive capabilities. 5 respondents representing 71.4% perceives the impact of technological advancements to significantly improve accuracy, 2 respondents representing 28.6% perceives the impact of technological advancements to moderately improve accuracy. The general acceptance of the impact of technological advancements to moderately improve accuracy indicates that Nigerian banks are aware of the value of technological advancements. This is why all banks have adopted one predictive analysis technique or other (as revealed in Table 4) and are

willing to explore more. However, Banks who represent the few percentages of moderate impact might have arrived at such conclusion because they are yet to fully explore the potential of such technological advancements.

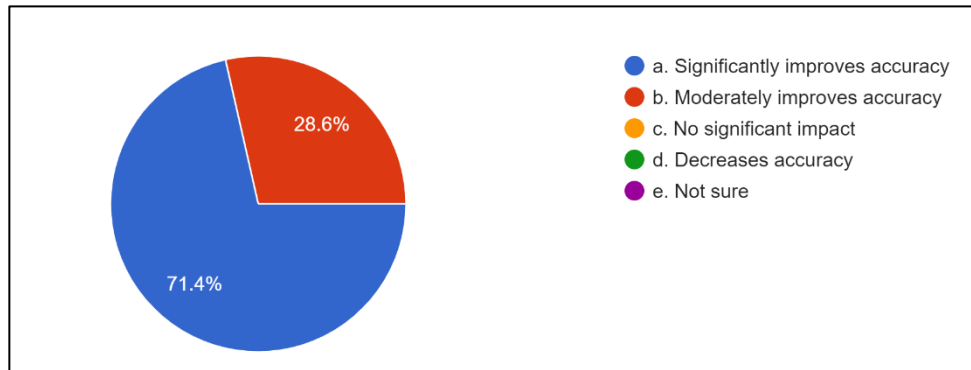


Fig 3: Chart showing the impact of technological advancements on predictive capabilities

4.2.4 Research Question Four: What is the relationship between predictive financial analysis and decision-making processes within banks?

- e. To what extent does predictive financial analysis influence decision-making processes within your bank?

Table 7: Frequency on the influence of predictive analysis on decision making process.

	Frequency	Percentage
Significantly influences	6	85.7
Moderately influences	1	14.3
Total	7	100.0

Table 7 data shows the extent to which predictive financial analysis influence decision-making processes within banks. 6 respondents representing 85.7% agreed that predictive financial analysis significantly influences decision-making processes within their banks while 1 respondent representing 14.3% agreed that predictive financial analysis moderately influences decision-making processes within their bank. It is apparent that respondents who agreed that predictive financial analysis significantly influences decision-making processes within banks were more in number. This response indicates that almost all the banks utilise predictive analytics in their decision making and have witnesses it effectiveness. This is indeed a remarkable shift from the traditional methods of decision-making process.

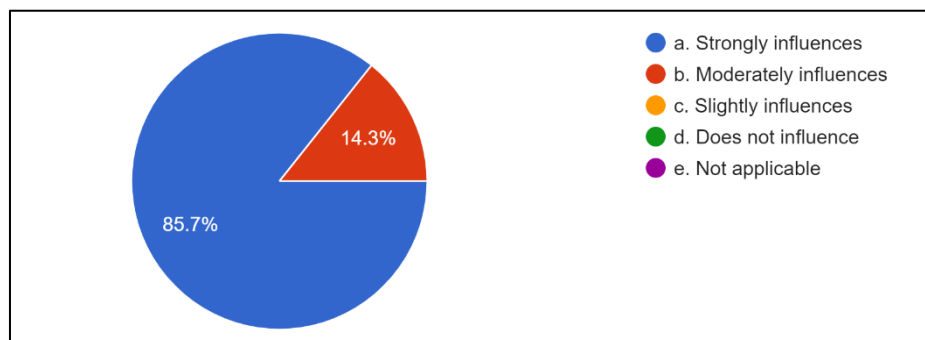


Fig 4: Chart showing the extent to which predictive financial analysis influence decision-making processes within banks

4.2.5 Research Question Five: What are the challenges and opportunities of predictive financial analysis in banks?

f. What are the primary challenges faced by your bank in implementing predictive financial analysis techniques? (Select all that apply)

Table 8: Data showing the primary challenges faced by bank in implementing predictive financial analysis techniques.

Banks	Factors	Frequenc y	Percentag e
First Bank, Fidelity Bank and Wema Bank	Data quality issues	3	42.9
Zenith Bank	Lack of expertise, Regulatory constraints, Integration with existing systems	1	14.3
Access Bank and First Bank	Data quality issues, Regulatory constraints, Integration with existing systems	2	28.6
Access Bank	Data quality issues, others	1	14.3
	Total	7	100.0

Table 8 data shows the primary challenges faced by bank in implementing predictive financial analysis techniques. The primary challenges faced by Access bank in implementing predictive financial analysis techniques include: Data quality issues, Regulatory constraints, Integration with existing systems and others. The primary challenges faced by Fidelity bank and Wema bank in implementing predictive financial analysis techniques include Data quality issues. The primary challenges faced by First bank in implementing predictive financial analysis techniques include: Data quality issues, Regulatory constraints, Integration with existing systems. The primary challenges faced by Zenith bank in implementing predictive financial analysis techniques include: Lack of expertise, Regulatory constraints, Integration with existing systems. Data from this table indicates that Data quality issues is a major challenge across all banks. However, the issue of data quality is not a challenge to Zenith. Lack of expertise is a challenge to Zenith Bank but not to other four banks. The major challenges that affect all five banks in this study is Regulatory Constraints and Integration with existing systems. This shows that banks have diverse strengths and weaknesses in terms of implementing predictive analysis technique.

- g. What opportunities lie in enhancing the use of predictive financial analysis in your bank? (Open-ended)

Table 9: Data showing opportunities that lies in enhancing the use of predictive analysis

Opportunities
<p>Accuracy in decision making</p> <p>Endless</p> <p>Helps finance professionals accurately forecast future outcomes and gain a competitive edge across several areas</p> <p>It can lead to a more efficient, customer-centric, and resilient banking operation.</p> <p>Mitigating financial and non-financial losses and enhancing security measures against fraud and other criminal acts that would affect the bank.</p> <p>Provides a competitive edge as well as mitigates financial losses and enhance security measures that needs to be taken</p> <p>The use of AI and Data Analytics will help in this regard</p>

Data in Table 9 shows the respondents opinion about the opportunities that lies in the use of predictive analysis. The opportunities as stated by the respondents includes: accuracy in decision making, endless opportunity, helps finance professionals accurately forecast future outcomes and gain a competitive edge across several areas, leads to a more efficient, customer-centric, and resilient banking operation, mitigating financial and non-financial losses and enhancing security measures against fraud and other criminal acts that would affect the bank, provides a competitive edge as well as mitigates financial losses and enhance security measures that needs to be taken and ultimately the use of AI and Data Analytics will help in this regard. Respondent from First Bank, Access Bank and Zenith Bank had similar opinion on the opportunities that lies in enhancing the use of predictive analysis. They believe it will enhance security measures and provide a competitive edge. Similarly, Fidelity Bank and Wema Bank believe it will bring about accuracy in decision making. A respondent in First Bank also believes that use of Artificial Intelligence will have a future potential.

4.2.6 Research Question Six: What are the perceptions and attitudes of people towards predictive analytics in decision-making

- h. How confident are you in the predictions generated by predictive financial analysis tools used in your bank?

Table 10: Frequency showing how confident banks are in the predictions generated by predictive financial analysis tools.

	Frequency	Percent
VERY CONFIDENT	5	71.4
MODERATELY CONFIDENT	2	28.6
Total	7	100.0

Table 10 data shows how confident banks are in the predictions generated by predictive financial analysis tools. 5 respondents representing 71.4% are very confident in the predictions generated by predictive financial analysis tools while 2 respondents representing 28.6% are moderately confident in the predictions generated by predictive financial analysis tools. The indication that majority are very confident with the predictions generated by predictive financial analysis tools shows that it works effectively and efficiently.

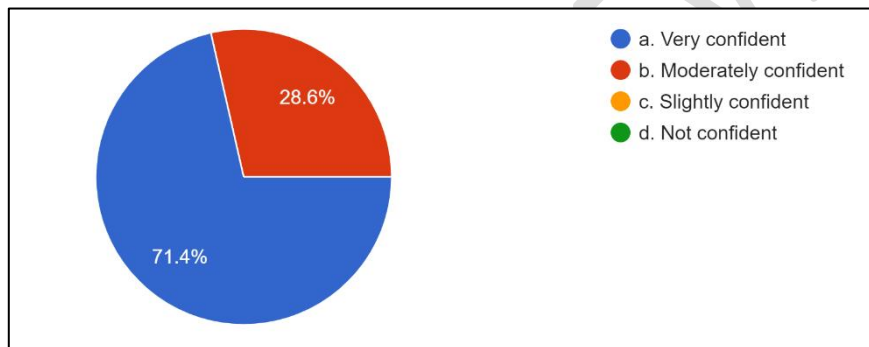


Fig 5: Chart showing how confident banks are in the predictions generated by predictive financial analysis tools

- i. How satisfied are you with the current predictive analytics capabilities of your bank?

Table 11: Frequency showing how satisfied banks are with current predictive analytics capabilities.

	Frequency	Percent
VERY SATISFIED	3	42.9
MODERATELY SATISFIED	4	57.1
Total	7	100.0

Table 11 data shows how satisfied banks are with current predictive analytics capabilities. 3 respondents representing 42.9% are very satisfied with current predictive analytics capabilities, while 4 respondents representing 57.1% are moderately satisfied with current predictive analytics capabilities. The satisfaction level percentage compared to confidence level (as showed in table 10) might be because the satisfaction level is based on capacity of the tool to analyse diverse data.

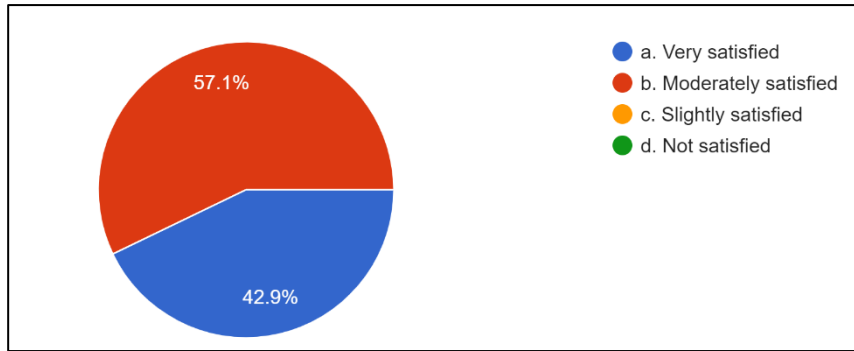


Fig 6: Chart showing how satisfied banks are with current predictive analytics capabilities.

j. What improvements or enhancements would you suggest for the predictive analytics capabilities of your bank? (Open-ended)

Table 12: Data showing suggestions on how predictive data analytics can be improved.

Suggestions
A lot of things can be added like revenue generated per customer
AI should be enhanced to help.
By feature engineering, algorithm selection, hyperparameter optimization, increasing dataset size, using ensemble methods, regularization, and cross-validation through use of AI
Humans trained to utilize the tools
None for now
To enhance predictive analytics in my bank, I suggest we improve data quality, adopt advanced tools, hire skilled analysts, and develop customized models for better risk management and customer insights.

Data in Table 12 shows the suggestions of respondents on how predictive Data Analytics can be improved. The suggestion as stated include; a lot of things can be added like revenue generated per customer, AI should be enhanced to help, By feature engineering, algorithm selection, hyperparameter optimization, increasing dataset size, using ensemble methods, regularization, and cross-validation through use of AI, humans should be trained to utilize the tools, improving data quality, adopting advanced tools, hiring skilled analysts, and developing customized models for better risk management and customer insights. However, two of the respondents had no suggestion. From data, some banks made similar suggestions. Zenith bank and First bank suggested that AI should be used as it will improve predictive

analytics. Wema Bank and Fidelity bank suggested that staff should be trained and equipped with necessary and required skill.

5. Findings from the Study

From the Data Description and analysis, the following were revealed in this study.

Most banks specifically Access Bank, Wema Bank and Zenith Bank utilise Predictive analysis Daily.

Most banks specifically Access, First Bank and Wema Bank rely on time series predictive analysis technique because of its accuracy in forecasting future financial trends

The common primary factors influencing the accuracy of predictive financial models in Banks are Quality of Input Data and Model Complexity.

There was a general acceptance that the impact of technological advancements moderately improve accuracy.

Respondents agreed that predictive financial analysis significantly influences decision-making processes within banks.

The major challenges that affect all five banks in this study is Regulatory Constraints and Integration with existing systems.

Opportunities that lie in the use of predictive analysis as stated by the banks include: accuracy in decision making, endless opportunity, helps finance professionals accurately forecast future outcomes and gain a competitive edge across several areas, leads to a more efficient, customer-centric, and resilient banking operation.

Respondents are very confident in the predictions generated by predictive financial analysis tools.

Respondents are moderately satisfied with current predictive analytics capabilities.

Respondents suggested that humans should be trained to utilize the tools, improving data quality, adopting advanced tools, hiring skilled analysts, and developing customized models for better risk management and customer insights. They also suggested AI should be used.

6. Discussion of findings

Findings in this study revealed that the major challenges affecting all five banks in this study are Regulatory Constraints and Integration with existing systems. However, the issue of data quality is relatively easy for Zenith. Lack of expertise is a challenge to Zenith Bank but not the other four banks. The major challenges that affect all five banks in this study are Regulatory Constraints and Integration with existing systems. This shows that banks have diverse strengths and weaknesses in implementing predictive analysis techniques. This is in line with the study of (Leo et al., 2019), who posited that one of the challenges of

implementing predictive financial analysis is data quality and availability. Similarly, it is corroborated by the study of Wamba et al. (2017), which revealed that another prominent challenge is a need for more data scientists and analysts with the requisite expertise.

Respondents are very confident in the predictions generated by predictive financial analysis tools. This shows that predictive financial analysis tools have proven to be effective. On the contrary, a higher percentage of respondents are moderately satisfied with current predictive analytics capabilities. The low score for satisfaction level suggests that banks should expand the capacity of their tool(s). This is justified by one of the recommendations from the banks, which is that banks should adopt advanced data tools.

Findings in this study revealed that most banks rely on time series analysis techniques to forecast future financial trends. This is against the study of Meryem et al. (2016), which revealed that various techniques used in predictive analysis are clustering, association rules, and regression analysis. Similarly, findings in this study also revealed that respondents perceive the impact of technological advancements to improve accuracy significantly. This is in line with the study of Gidiagba et al. (2024), which revealed that technological advancements in predictive analysis have led to more accurate and timely maintenance interventions, contributing to enhanced system durability and operational efficiency.

7. Conclusion and Recommendations

Based on the findings in this study, it was concluded that the primary challenges faced by banks in implementing predictive financial analysis techniques include data quality issues, regulatory constraints, lack of expertise, integration with existing systems, and others. Similarly, most banks rely on time series analysis techniques to forecast future financial trends. The findings in this study also revealed that respondents perceive the impact of technological advancements to improve accuracy significantly. Therefore, the following recommendations were made;

1. A robust data management system practice should be established to ensure the accuracy and consistency of data. This will help the banks with the issue of data quality.
2. Continuous training and development programs should be made available for staff to reduce the problem of Lack of Expertise.
3. Integration between the existing system and the new predictive analytics method should be prioritized.
4. Beyond time series analysis, banks should explore other predictive analytics techniques to enhance forecasting accuracy.
5. Banks should partner with Fintech companies specializing in predictive analytics to benefit from their expertise.

8. Limitation of the Study

While conducting this study, the researcher encountered some unavoidable limitations. Time constraints were one of the significant limitations of this study. Another area for improvement is the unavailability of data analysts at various bank branches. Respondents at the bank's head office seemed always busy and could only spare a few minutes. This made the research focus on only five banks. However, subsequent studies should focus on more banks for adequate information.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

UNDER PEER REVIEW

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