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

Abstract:

This study examined the techniques, impacts and challenges of predictive financial analysis in Nigeria Banking Institutions. The study adopted a descriptive survey research design. Simple random sampling technique was used to select 7 respondents to represent five banks (Access Bank, Fidelity Bank, First Bank, Wema Bank and Zenith Bank). A self-designed developed online questionnaire (SDOQ) was used for data collection. Data collected were analysed using descriptive statistics (percentage). Findings of the study revealed that the primary challenges faced by bank in implementing predictive financial analysis techniques include; data quality issues, regulatory constraints, lack of expertise and integration with existing systems and others. Similarly, most banks rely on time series analysis technique to forecast future financial trends. It was therefore recommended that a robust data management system practice should be established to ensure accuracy and consistency of data. Also, beyond time series analysis, banks should explore other predictive analytics techniques to enhance forecasting accuracy.

Keyword: Predictive Financial analysis, Technological advancements, Nigeria Banks.

1. Introduction

The Nigerian Banking Institutions is the life wire of the nation's economy. They play a vital and huge role in the nation's economic development and financial system. The role of these institutions remains a catalyst towards 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. 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, Nigeria banks still face challenges in predicting financial performance (Fadun & Oye 2020; Gwaison & Maimako 2021).

Over the years, works of literature have revealed that banks relied on traditional analytical method whose purpose was 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 in order 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 on 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).

The advent of predictive analysis has therefore addressed these limitations by introducing models capable of analyzing a broader spectrum of variables, thereby 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 that are reshaping the landscape of financial analysis and decision-making processes in banks (Addy et al., 2024; Farayola et al., 2024). This trend according to Addy et al., (2024) involves the integration of predictive analytics across diverse banking operations. Banks are extending the use of predictive models beyond traditional risk assessment to include areas such as customer segmentation, fraud detection, and personalized product offerings (Devan et al., 2023; Addy et al., 2024). This trend of integration 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 the transformative impact of these technologies in enhancing the analytical capabilities of banks. 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 and Larasati 2023). The banking sector's approach to predictive analysis is characterized by a move towards advanced modelling techniques, broader application across operations, democratization of tools, and heightened ethical and regulatory awareness. These trends, as revealed by the review, indicate an expanding role for predictive analysis in banking, shaping future strategies and decision-making processes.

Predictive analysis in banking could be seen as a representation of change in how financial institutions makes decision, manages 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 important aspect of predictive analysis lies in its ability to process wide amounts of data to reveal information and trends that are not immediately apparent. 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 have significant implications for 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 not only improves efficiency but also 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 analyses and predictive analysis 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 that are informed by data-driven insights, thereby 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) provides a comprehensive analysis of 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 faced by Islamic banks, 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 that align with both 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, but to the best of the author's knowledge, majority have not focused on techniques and challenges most especially in the Nigeria Banking Institutions. 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). These challenges among others 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). 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 of this, 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 analyze 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 a huge number of variables. This analysis could be used by organizations to achieve their desired goals and increase their profits. In support of this view, Hoda et al., (2016), defined predictive analytics as a prediction of the future by analyzing the past performance and studying the historical data to uncover the relationships and patterns in these data. (Prasadababu and Hanumanth, 2014) added that predictive analytics help organizations' in predicting risk, tendency, and in attaining better revenues by enhancing their key metrics and making strategic corrections and this is by making accurate predictions from structured and unstructured information. Actually, those predictions are done based on models and techniques.

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

Classification: decisive outcome, it's for predicting the value of decisive variable (class or target) by constructing a model based on one or multi 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 coming from a manufacturing line.

Clustering (unsupervised learning): assigning observations into clusters, each cluster contains the similar observations and data. This process helps in discovering the 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 from one another. An example of clustering is creating a set of consumer segments based on data about individual consumers, including demographics, preferences, and buyer behaviour.

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

Furthermore, the association rule is a rule-based machine-learning approach for finding out interesting relationship 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 which contain X tend to contain Y. Association rules applied for market basket analysis. An example of such a rule might that 98% of customers that purchases tires and automobile accessories also have automotive carried out.

Regression: numerical outcome, predicting the value of target (numerical variable) by constructing a model based on one or more predictors (numerical and categorical variables). On the other hand, regression is useful for predicting outputs that are continuous. That means the answer to your question is represented by a quantity that can be flexibly determined based on the inputs of the model rather than being confined to a set of possible labels.

2.2 Impact of technological advancement on predictive capabilities

The revolution of technology has serious impact on predictive capabilities because it has been revolutionized by significant technological advancements. These developments have expanded the capabilities of predictive analysis, making it a critical tool across various sectors, including finance. Predictive analysis has been provided with a rich source of information with the advent of big data. Coupled with advent 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), in the pharmaceutical industry, big data predictive analytics and radio frequency identification technology are being used 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 field, even in supply chain management, particularly among small and medium-sized enterprises (SMEs). In line with this, the study of (Sodero et al., 2022) have shown that technological factors such as relative advantage and compatibility play substantial roles in the adoption of predictive supply chain business analytics. This adoption is driven by the need to improve efficiency, reduce costs, and enhance decision-making processes. This technological advancements on predictive analysis has led to more accurate and timely maintenance interventions, contributing to enhanced system durability and operational efficiency (Gidiagba et al., 2024). In spite of these advancements, the field of predictive analysis faces challenges, particularly in terms of data privacy, ethical considerations, and the need for financial cast.

2.3 Challenges of Predictive analysis

One of the challenges predictive analysis as opined by (Leo et al., 2019), is data quality and availability. The efficacy of predictive models usually depends on the quality and quantity of data. Most banks often encounter 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 a shortage of 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 and 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 face constraints in terms of 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 and 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 pattern;

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 series of inquiries to individuals who took part in the study and summarized their responses. This study's target population comprised of all banks in Nigeria. The sample size included 7 individuals who were 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/1Kvl3kw9llRqqCBmw7LdZsVr4JXicVFkWwQy9ulB8s0M). The online questionnaire consisted of 10 questions; 8 of which contain options to be chosen from while the remaining two were open ended questions. Data Collected was analysed 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**

Data in table 1 shows the different capacities where respondents work. It is evident that 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. It is apparent that respondents who works in Access Bank and First Bank were more in numbers. 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	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. Zenith Bank and Wema Bank from this data has been seen to use predictive analysis daily. This indicates the effectiveness of using predictive analysis for forecasting future financial trend. However, Access bank from the data revealed that they use predictive analysis Daily and Monthly. This might have to do with the years of experience of the respondents giving the information. Access bank might have moved from monthly to daily to enhance accuracy while the respondents giving the information might not be aware (due to promotion from local branch to head office). Similarly, First bank used predictive analysis monthly and occasionally. This indicated variations in analytical frequency within the bank which is a weakness. Therefore, it can be said that most banks utilise Predictive analysis Daily.

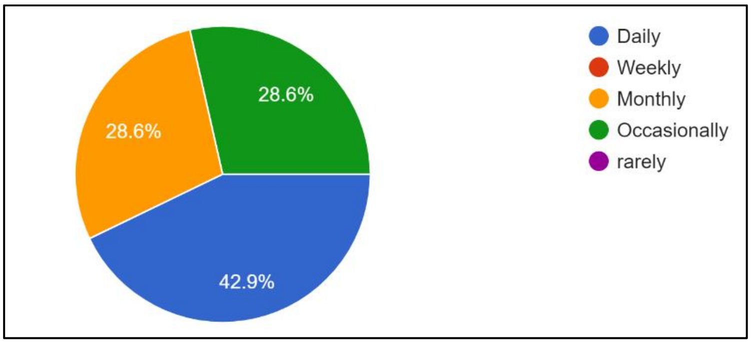

Fig 1: Chart showing how frequently bank utilizes predictive analysis for forecasting of future trends

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.

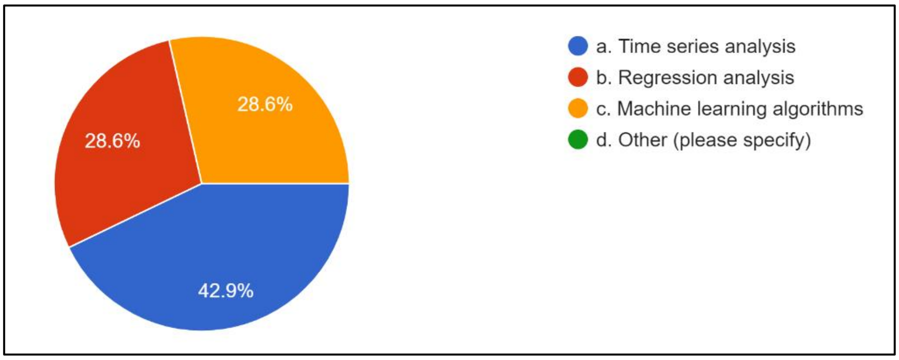

Fig 2: Chart showing predictive analysis techniques bank primarily rely on for forecasting future financial trends

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.

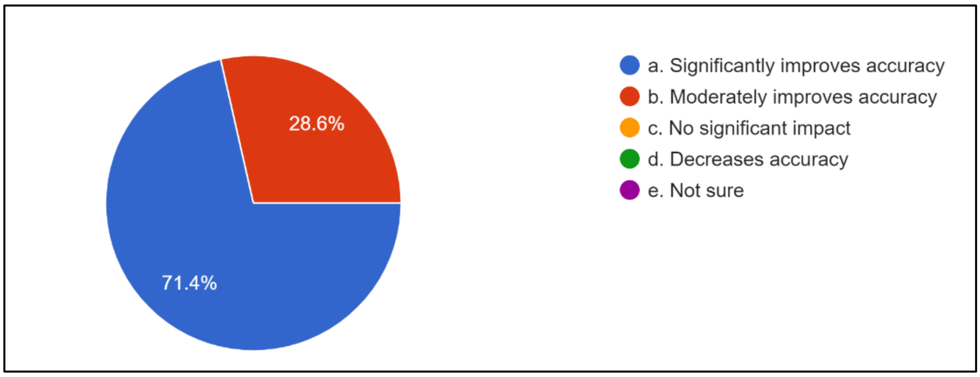

Fig 3: Chart showing the impact of technological advancements on predictive capabilities

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.

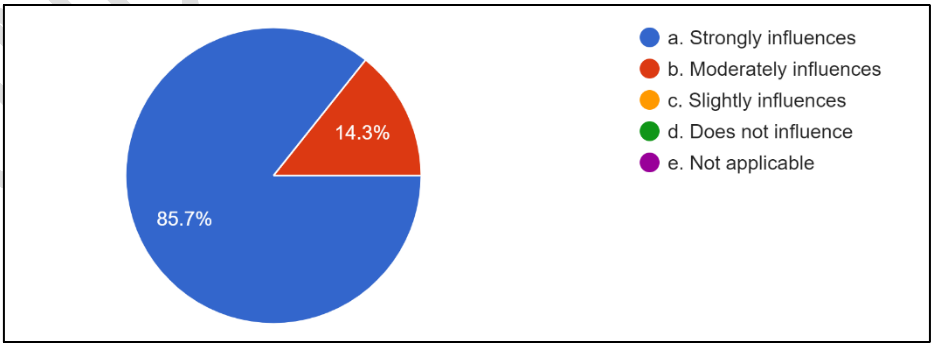

Fig 4: Chart showing the extent to which predictive financial analysis influence decision-making processes within banks

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**	**Frequency**	**Percentage**
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
Accuracy in decision making
Endless
Helps finance professionals accurately forecast future outcomes and gain a competitive edge across several areas
It can lead 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
The use of AI and Data Analytics will help in this regard

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.

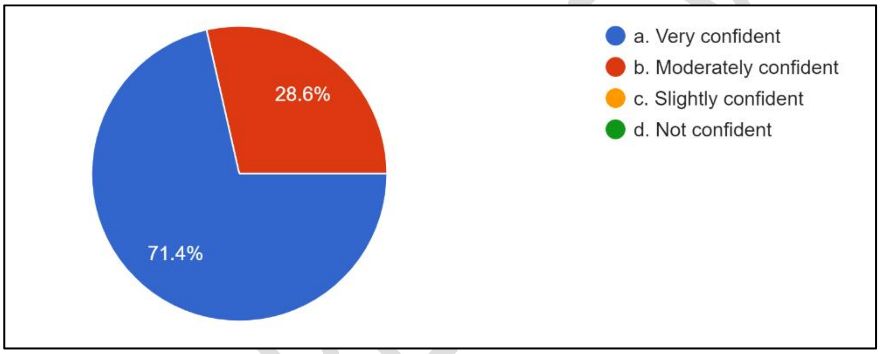

Fig 5: Chart showing how confident banks are in the predictions generated by predictive financial analysis tools

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.

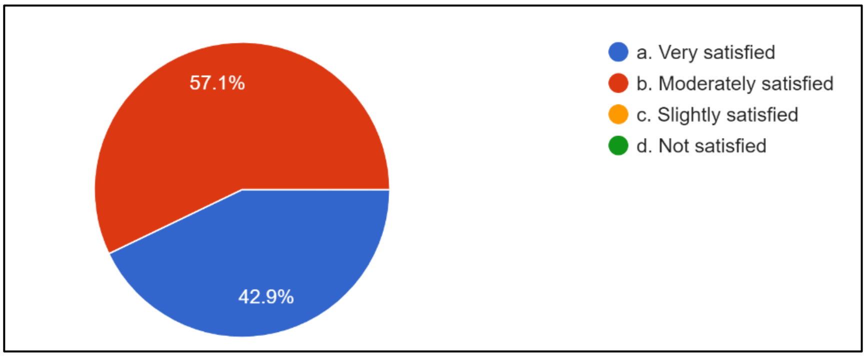

Fig 6: Chart showing how satisfied banks are with current predictive analytics capabilities.

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.

The 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 lies 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 among others in this study revealed that the major challenges that affect all five banks in this study is Regulatory Constraints and Integration with existing systems. 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. 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 also in corroboration with the study of Wamba et al. (2017), which revealed that another prominent challenge is a shortage of 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. In contrary, higher percentage of respondents are moderately satisfied with current predictive analytics capabilities. The low score for satisfaction level tentatively suggests that banks should expand the capacity of their tool(s). This is justified by one of the recommendations from the banks that banks should adopt advanced data tools.

Findings in this study revealed that most banks rely on time series analysis technique to forecast future financial trends. This is against the study of Meryem et al., (2016) which revealed that various techniques used in the 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 significantly improve accuracy. This is in line with the study of Gidiagba et al., (2024) which revealed that technological advancements on predictive analysis has 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 bank in implementing predictive financial analysis techniques include; data quality issues, regulatory constraints, lack of expertise and integration with existing systems and others. Similarly, most banks rely on time series analysis technique to forecast future financial trends. Also, findings in this study also revealed that respondents perceive the impact of technological advancements to significantly improve accuracy. Therefore, the following recommendations were made;

1. A robust data management system practice should be established to ensure accuracy and consistency of data. This will help the issue of data quality faced by banks
2. Continuous training and development programs should be made available for staff to reduce the problem of Lack of Expertise.

3. Integration between existing system and new predictive analytics method should be prioritize.
4. Beyond time series analysis, banks should explore other predictive analytics techniques to enhance forecasting accuracy.

5. Banks should partner with Fintech companies specialising in predictive analytics in order to benefit from their expertise.

8. Limitation of the Study

While conducting this study, the researcher encountered some limitations which were unavoidable Time constraint was of the significant limitations in this study. Unavailability of data analyst at various bank branches is another limitation. Respondents at banks head office seems to always be busy and could only spare few minutes of their time. This made the research focused on only five banks. However, subsequent study should try to 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.

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