The use of Artificial Intelligence for Business Optimisation in Banking: Case of Nigeria

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Abstract

Background: The continuous increase in the amount of customer data stored by commercial banks necessitates the use of artificial intelligence (AI) technologies. AI technologies may be used for analysing customer data and predicting customer behaviour, with the aim of customer retention and satisfaction. Such technologies include machine learning algorithms and deep learning models. Commercial banks in Nigeria are employing these predictive analysis tools. However, not all Nigerian commercial banks currently use them.

Objective: The objective of this study is to explore how Nigerian commercial banks use AI technologies for business optimisation.

Methodology: This study was interpretivist, abductive, and followed a qualitative approach deploying a multiple case study design. This study used the Organisational information processing (OIP) theory as a theoretical framework. Through the concept of matching information processing capabilities to information processing needs, the study explored the use of AI in Nigerian commercial banks. The multiple case study design consisted of three banks, selected from a total of nineteen commercial banks. A purposive sampling approach was used to select 20 experienced data professionals from business intelligence (BI) departments of the selected banks. Data was collected through semi-structured interviews. The study used thematic analysis to analyse the data.

Findings: Findings show that information processing needs such as customer and data needs motivated commercial banks to utilise AI technologies as information processing capabilities. AI technologies such as the Sentiment intensity analyser, LR, K-means algorithm, Naïve Bayes algorithm, K-nearest neighbour, and Recommendation engines, were used for various tasks. For example, sentiment analysis, customer segmentation, customer churn prediction, predicting loan collection credibility and product recommendations. Findings also show that deep learning models were not used by the commercial banks, due in part to a lack of computational resources

Contribution: The research confirmed that the use of AI in commercial banks in Nigeria contributes to customer retention and satisfaction. It provided knowledge of how AI technologies were used by commercial banks. This knowledge is important for other banks in Nigeria that may eventually use AI technologies due to the constant growth of customer data. The study also refined the organisational information processing theory to capture the findings. The refined version was titled ‘Nigerian Commercial Bank Information Processing View’.

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List of Acronyms

AI	Artificial intelligence
ANN	Artificial neural networks
ATM	Automated teller machine
BI	Business intelligence
Bi-LSTM	Bidirectional long short-term memory
BNB	Bernoulli naïve bayes
CART	Classification and regression trees
CBN	Central Bank of Nigeria
CNN	Convolutional neural networks
DL	Deep learning
DNN	Deep neural network
DOI	Diffusion of innovation
DT	Decision tree
KNN	K- nearest neighbour
KPMG	Klynveld Peat Marwick Goerdeler
LR	Logistic regression
LSTM	Long short-term memory
ML	Machine learning
MLP	Multilayer perceptron
MTN	Mobile telephone network
NLP	Natural language processing
OIP	Organisational information processing
POS	Point of sale
RNN	Recurrent neural networks
SET	Social exchange theory
SME	Small and medium- sized enterprises
SQL	Structured query language
SSIS	SQL server integration services
SSRS	SQL server reporting services
SVC	Support vector classifier
SVM	Support vector machine
TAM	Technology acceptance model

Glossary

Terms	Definition
Artificial intelligence	The science of developing machines that can think like humans
Artificial neural network	Artificial neural networks consist of artificial neurons that loosely mimic the neurons in the brain
Automated teller machine	A machine that is used to collect cash and make transfers
Business intelligence	Strategies and technologies used by organisations for data analysis and business information management
Bidirectional long short-term memory	A type of recurrent network that processes sequential data in both forward and backward directions
Bernoulli Naïve Bayes	It is based on the Bernoulli distribution and accepts only binary values of 0, or 1
Classification and Regression trees	A machine learning algorithm used for predicting categorical data
Convolutional neural network	A regularised type of feed-forward neural network that learns features automatically
Deep neural network	A neural network containing several layers, input, output and one or more hidden layers.
Decision tree	A non-parametric algorithm useful for classification and regression tasks
Long short-term memory	A type of recurrent neural network capable of processing sequential data
Multilayer perceptron	A fully connect feed-forward artificial neural network with an input, output, and hidden layer
Point of sale	The area in which a financial transaction action occurs, usually through a credit card terminal
Recurrent neural network	A deep learning model capable of processing and converting sequential data input into a specific sequential data output
Support vector classifier	Supervised machine learning methods used for classification, regression and outlier detection
Support vector machine	Supervised machine learning methods used for classification, regression and outlier detection

Chapter 1 : Introduction

Business optimisation is a major goal for any organisation (Petit, 2016). It is a process of refining procedures and tasks in an organisation to improve efficiency, financial performance, and increase profit margins (Petit, 2016). Businesses largely depend on business optimisation to ensure that they meet their strategic goals and stay ahead of their competitors (Kasych et al., 2019). The continuous increase in data drives the need for optimisation, and when data are properly analysed, it can result in key insights for effective and efficient decision-making (Ahmad et al., 2023). In the banking industry, the refinement of processes and procedures are geared towards customer retention and satisfaction (Hanaysha & Mehmood, 2022; Kumar et al., 2022; Nithya & Kiruthika, 2021). Banks rely on strategies and technologies to continuously meet the varying and growing needs of their customers (Kumar et al., 2022). The needs of customers are important, because they make up the backbone of the existence of the banking industry, and their satisfaction is pivotal to ensuring the maintenance of an organisation's competitive advantage (Hanaysha & Mehmood, 2022).

Technologies such as Business intelligence (BI) tools and Artificial intelligence (AI) systems have the potential to assist banks in analysing data for customer satisfaction. In Nigeria, the banking sector makes use of these technologies frequently in the country (Borokini et al., 2023; Ukpong, 2022). The Nigerian banks use these technologies to analyse large datasets, and gain useful information, to improve customer service. These technologies also provide the banks with a wide range of capabilities that enable them to add new functionality to their various client platforms, contributing to customer retention and satisfaction (Agidi, 2019).

This study aimed to explore the use of AI technologies in Nigerian commercial banks for customer retention and satisfaction. This chapter provides the background information about this study, followed by the problem statement, the research questions and objectives, and the scope and significance of the research. The chapter also presents an overview of the research approach, and of chapters.

1.1 Background to the study

1.1.1 BI and AI technologies in the banking industry

BI technologies enable organisations to tell a data-driven story, by gleaning useful information from data stored in a database and presenting it in an informative manner. The information obtained from data is used to make informed decisions about customers, and improves productivity and sales (Ayoubi & Aljawarneh, 2018). The Banking industry in Nigeria has benefited from the utilisation of BI technologies in terms of improved customer relationships (Nithya & Kiruthika, 2021). Small and medium-sized enterprises (SMEs) have also employed BI technologies for the optimisation of overall business performance (Lateef & Keikhosrokiani, 2022). Examples of BI technologies used by banks include Microsoft Power BI and Tableau for data visualisation; Sisense for analysis and visualisation of large datasets; Dundas BI for data visualisation, and Pentaho for data integration and analytics (Tavera et al., 2021).

Banks rely on BI technologies for information processing and information sharing. Adequate processing of information leads to high-quality results and improved performance, which are all benefits of the business optimisation process (Tavera et al., 2021). However, the complexities within the business environments make it challenging for these organisations to continue to process information for key decision-making (Tavera et al., 2021). The growth of customer data both in structured and unstructured formats, is one of such complexities that presents banks with the daunting challenge of getting accurate analytical results (Schmitt, 2023; Tamang et al., 2021). BI technologies are more suitable for descriptive analysis and fail to accurately make predictions from large volumes of data (Zohuri & Moghaddam, 2020). For example, customer feedback data requires data mining techniques to discover patterns in the datasets to enable businesses to make more informed decisions based on their customer needs (Hamzehi & Hosseini, 2022; Tamang et al., 2021). Banks, therefore, require predictive analytics technologies to analyse large customer datasets and anticipate the needs and behavioural patterns of customers. This is important for improving customer value and improving relationships with passive customers (Desai et al., 2021).

The field of AI consists of such predictive analytics technologies that enable organisations to stay abreast with the data developments of the 21st Century (Schmitt, 2023). AI involves the development of technologies that can adapt to different environmental conditions. These technologies are capable of making inferences, thinking, comprehending, and learning to be able to predict future outcomes (Sharda et al., 2021). AI technologies provide benefits to organisations such as: providing more accurate results in sales forecasting, trend analysis, and non-linear data analysis (Tamang et al., 2021). These technologies are also useful for analysing customer data in banks, to determine what products or items customers would like to buy. This enables informed decision-making in terms of which products to promote, to boost sales and maintain good customer relationships (Desai et al., 2021).

1.1.2 AI in Nigeria

The adoption and implementation of AI is growing rapidly on the African continent (Ade-Ibijola & Okonkwo, 2023). Nigeria is one of the leading countries concerning AI on the African continent (see Table 1-1). The country has implemented initiatives such as the Centre of AI and Robotics, and established research communities like data science Nigeria (Gwagwa et al., 2020). Nigeria is one of the few countries on the continent that has achieved some success in adopting and implementing AI technologies (Alupo et al., 2022). These technologies require the use and availability of large datasets and the technical know-how of their adopters to be able to use and deploy them (Gadzala, 2018). Furthermore, customers must be comfortable with these technologies and be assured of the privacy and security of their data by the organisations that have adopted AI technologies (Gadzala, 2018).

Nigeria has been able to navigate these issues to a considerable extent, resulting in scalable deployments of AI technologies in the areas of agriculture, telecommunications, and, most notably by financial institutions (Alupo et al., 2022; Gadzala, 2018; Ukpong, 2022). For example, chatbots like Kudi, which is integrated into the Facebook messenger app, help facilitate mobile banking for users who may not have mobile banking applications or are unfamiliar with internet banking (Gadzala, 2018). Online facilities and data-driven platforms such as Konga and Zenvus are other examples of the use of AI technologies in Nigeria (Ade-Ibijola & Okonkwo, 2023).

The support of the government has also been pivotal in enabling the adoption and use of AI technologies in Nigeria. The Nigerian government implements policies and rules that bring trust to customers and govern the ethical use of such technologies (Gadzala, 2018). Policies like the Data Protection Act ensures the safety, privacy, and security of customer data in the banking industry (Oyewole & Salami, 2024). Since Nigeria is one of the highest users of AI technologies in Africa, it is suitable to provide information about the use of AI technologies. Table 1-1 shows the number of companies that specialise in AI by country, in Africa.

Table 1-1: Number of companies specialised in AI by country (Jaldi, 2023)

African Countries	Number of Companies that Specialise in AI
South Africa	726
Nigeria	456
Egypt	246
Kenya	204
Morocco	126
Ghana	115
Tunisia	103
Cameroun	54
Tanzania	44
Uganda	44
Zimbabwe	44
Mauritius	35
Ivory Coast	29
Algeria	26
Senegal	23
Rwanda	21
Zambia	20
Ethiopia	18
Botswana	16
Republic Democratic of Congo	10

1.1.3 Drawbacks of AI technologies

Despite the benefits provided by AI; they are not without faults. When it comes to implementing Machine learning (ML) techniques, companies can encounter problems such as pinpointing the right datasets to feed into the algorithms and choosing the right algorithms for the corresponding problem (Desai et al., 2021). Deep learning (DL) models are complex in nature and are not easy to explain. They also require a high volume of data, and high computational cost (Ahmed et al., 2023). The rate at which these technologies are growing has also triggered ethical concerns, which arise due to the human-like capabilities that these technologies possess. They also have no conscience for the establishment of moral or ethical boundaries when performing activities that require the collection of personal data (Enholm et al., 2022). Other issues such as data privacy and explicability are also critical when it comes to implementing ML algorithms and DL models (Benbya et al., 2020). Nonetheless, these technologies pose great benefits to banks when used appropriately for the right tasks.

1.1.4 Justification for selecting the Nigerian banking sector

The banking sector in Nigeria was selected for this study for the following reasons:

- The Nigerian banking sector promotes financial inclusion by providing financial services to a wide variety of customers with financial innovations such as; automated teller machines (ATMs), point-of-sale (POS) terminals, and mobile and internet banking (Oyadeyi, 2024). Nigerian banks therefore make a significant contribution to the nation's economic and sustainable growth, with financial inclusion identified as a catalyst for seven of the 17 sustainable development goals globally (Oyadeyi, 2024).
- The banking sector in Nigeria is part of the services sector, which accounted for 56.18% of the country's gross domestic product in the year 2023 (C.B.N, 2024). This further highlights the contribution of the banking sector in Nigeria to economic growth in the country.

1.1.5 Suitability of banks as cases

This study used a multiple case study design, which consisted of three commercial banks selected from 19 commercial banks in Nigeria. The suitability of commercial banks as cases was based on two reasons:

- Commercial banks in Nigeria use AI technologies for customer retention and satisfaction (Borokini et al., 2023; Ukpong, 2022).
- Commercial banks in Nigeria are one of the most frequent employers of predictive analysis tools (KPMG, 2019). These tools are used to determine patterns and gain useful insights from customer data for the prediction of customer behaviour.

The headquarters of the commercial banks were selected as opposed to the branch offices. Headquarters were more suitable because they had more robust departments and staff than the branch offices and could provide the information needed for the study (Odunlami & Oludipe, 2021).

1.2 Research problem

Previous research on AI in the Nigerian banking industry mainly focused on listing the technologies used in the banks, and the outcome obtained from using the technologies (Borokini et al., 2023; Ukpong, 2022). There is dearth in literature about how these technologies are used by commercial banks, in the Nigerian banking industry.

There remains a growing interest in AI technologies, in the Nigerian banking industry. Nigerian banks need to utilise these technologies to effectively analyse expansive amounts of customer data, for customer retention and satisfaction (Borokini et al., 2023; Ukpong, 2022). However there remains the issue of having the proper knowledge of which technologies to use for certain tasks (Desai et al., 2021; Neumann et al., 2022). A few commercial banks in Nigeria, currently use AI technologies. However, due to the knowledge gap about how these technologies are used, other banks are unable to utilise them (Ajayi & Olalekan, 2023). Hence the use of AI technologies in Nigerian commercial banks remains at a minimal level (Ajayi & Olalekan, 2023).

1.3 Research purpose

There is a lack of knowledge about how AI technologies are used in the Nigerian banking industry. This has the consequence of preventing the widespread use of these technologies. The purpose of this research, therefore, was to explore how commercial banks in Nigeria used AI technologies for customer retention and satisfaction.

1.4 Research questions and objectives

The main research question, and two sub-questions along with their corresponding objectives for the study are presented in Table 1-2.

Table 1-2: Research questions and objectives

Research Questions	**Research objectives**
Main research question How do commercial banks in Nigeria use AI technologies for business optimisation?	Main research objective To explain how commercial banks in Nigeria use AI technologies for business optimisation.
Sub-questions a) What motivates Nigerian commercial banks to use AI technologies? b) What AI technologies do Nigerian commercial banks use for business optimisation?	Sub-objectives a) To identify the needs that motivate Nigerian commercial banks to use AI technologies. b) To identify the AI technologies that Nigerian commercial banks use for business optimisation.

1.5 Scope of the research study

This research explored how commercial banks in Nigeria used AI technologies for business optimisation. Data professionals were the subject matter experts in this research. These data professionals worked in the BI departments of the banks. The study interviewed the data professionals to get information regarding the needs that motivated the banks to utilise such technologies, the current technologies used, and descriptions of how these technologies were used for certain tasks.

This study also focused on the outcome of business optimisation in the banking industry, which is customer retention and satisfaction. Hence business optimisation is consequently referred to as an outcome in terms of customer retention and satisfaction. Also, words such as ‘machine learning algorithms’ and ‘machine learning models’ are used interchangeably.

1.6 Significance of the research study

The constant growth of customer data has pushed various organisations in Nigeria to use AI technologies (Busayo et al., 2023; Ukpong, 2022). Nigerian commercial banks currently use AI technologies to analyse customer data, and predict customer behaviour, for customer retention and satisfaction (Borokini et al., 2023; Ukpong, 2022). However, not all commercial banks in Nigeria currently use AI technologies, due to the lack of knowledge of how these technologies are used (Ajayi & Olalekan, 2023).

As customer data continues to grow, it is paramount that commercial banks in Nigeria use AI technologies to analyse such data for customer retention and satisfaction; as these technologies are efficient for the analysis of large amounts of customer data (Desai et al., 2021; Hamzehi & Hosseini, 2022). Therefore, this study poses the significance of providing knowledge on how AI technologies are used for customer satisfaction and retention. This knowledge will help to inform other banks who may eventually use AI technologies due to the constant growth of data.

1.7 Overview of research approach

This study was interpretivist, abductive, and followed a qualitative approach deploying a multiple case study design. This study also employed a relativist ontology, and a constructivist epistemology. This study used the Organisational information processing theory as a theoretical framework. The study explored the use of AI in Nigerian commercial banks, through the concept of matching information processing capabilities to information processing needs. The multiple case study design consisted of three banks, selected from nineteen commercial banks. The target population of the study were data professionals, who served as the subject matter experts for this study. The study used A purposive sampling approach to select the most experienced data professionals. Data was collected through semi-structured interviews over a cross-sectional timeframe, and thematic analysis was used to analyse the data collected.

1.8 Organisation of the dissertation

The rest of the dissertation is organised as follows:

Chapter 2 provides past literary works related to the research study. The chapter further defines the key terms in the research topic and gives an overview of AI technologies employed by organisations within and outside the context.

Chapter 3 provides the theoretical foundation for the research study and discusses the suitability of the theory for the research study.

Chapter 4 discusses the methodology and design of this study.

Chapter 5 provides information about the Nigerian banking industry and describes the selected cases for this study.

Chapter 6 reports the research findings, answers the research questions, and presents a refined version of the theoretical framework used in this study.

Chapter 7 discusses the research findings, and their relation to the literature.

Chapter 8 concludes the research study, and provides the implications, contributions, limitations of the study and future suggestions.

Chapter 2 : Literature Review

This chapter provides past literary work on the research topic. The chapter begins by defining AI technologies and providing examples of various AI technologies. Further, the chapter explains the steps taken to analyse customer data using AI technologies and highlights the drawbacks of AI technologies. The chapter summarises studies on the use of AI and BI technologies in banks and other organisations in Nigeria. The chapter also summarises the use of AI technologies by banks in other countries and presents the gap in the literature.

2.1 Artificial intelligence

AI can be defined as a set of systems that aid decision making by providing the technological tools required for ingesting, processing, and analysing information stored in databases, quickly and accurately (Ahmad et al., 2023). AI consists of two subsets: ML algorithms and DL models. The former can learn from the data given to them to predict future scenarios (Çelebi, 2021). On the other hand, the latter are a subset of ML that is based on neural network models. They can learn from a vast amount of data and have shown great success in predictive analysis and forecasting (Desai et al., 2021).

The use of AI has a positive impact on digital transformation and the transformation of capabilities within organisations. Organisations use AI to improve their technological or information processing capabilities, as a step toward processing vast amounts of information, retaining competitive advantage and meeting customer demands (Ahmad et al., 2023).

2.1.1 Classification of AI based on intelligence and capabilities

The term 'intelligence' represents the ability of technologies to respond to certain prompts and signals. Based on intelligence, AI technologies can be classified into four categories: spatial, linguistic, social, and cognitive (Kaur & Mohta, 2019). Spatial intelligence is the ability of AI technologies to receive and understand visual information. Linguistic intelligence is the ability of these technologies to speak different languages and understand symbols. Social intelligence is the ability to respond properly to certain emotions, and cognitive intelligence refers to the ability to solve complex problems (Kaur & Mohta, 2019).

AI can be classified into three types based on capabilities: narrow, general, and super AI (Ameen et al., 2022). Narrow AI is the most accessible type of AI. It can be used to perform tasks intelligently, and functions within the boundaries of the task it is programmed to perform. Narrow AI is used for tasks such as picture identification, speech recognition, and in voice recognition technologies like Apple Siri (Ameen et al., 2022).

General AI relates closely to human intelligence. It consists of technologies that can adapt and learn on their own (Ameen et al., 2022). However, even with the proliferation of AI technologies in the world today, the creation of AI technologies that can execute tasks exactly like humans, without human intervention, has not yet been achieved (Dennehy et al., 2023). Therefore, researchers have focused their efforts on the creation of robots that can perform certain general AI tasks (Ameen et al., 2022).

Super AI, also called futuristic AI, is the potential creation of AI technologies that might outsmart humans (Ameen et al., 2022). The prospect of this kind of AI has sparked many moral, ethical, and privacy concerns (Enholm et al., 2022). These concerns have risen due to the human-like capabilities these technologies would possess. Also, the lack of conscience for establishing moral or ethical boundaries when performing activities that require the collection of personal data (Enholm et al., 2022)

2.1.2 Classification of AI based on models

The most common AI computational models are expert systems, neural networks, natural language processors, fuzzy logic, ML algorithms, and DL models (Sadiku et al., 2020). This research study focused on ML algorithms and DL models. The functions of these computational models are shown in Table 2-1.

Table 2-1: AI computational models and their functions (Sadiku et al., 2020; Sharma & Srinath, 2019)

AI computational model	Function
Expert systems	Expert systems function based on rule-based inferences and use rules to process and interpret data
Neural networks	Neural networks learn from patterns in existing datasets and use that information to make predictions when presented with new datasets
Natural language processors	Natural language processors are technologies that can be used for speech recognition, text analysis, language translation, and chatbots
Fuzzy logic systems	Fuzzy logic systems work with incomplete data and mimic human reasoning to provide estimates based on incomplete information
ML algorithms	ML algorithms learn from past data to make future inferences
DL models	DL models are a subset of ML that are adept at navigating more complicated problems

2.2 Machine learning algorithms

ML algorithms can be used to solve complex problems by automatically building models for these problems using available data (Baştanlar & Özuysal, 2014). ML algorithms are trained with datasets to build computational models and gain knowledge about the relationship between input and output variables. This knowledge is then used to forecast or predict future results or values (Baştanlar & Özuysal, 2014).

ML is a process that requires the provision of datasets, an objective, and an optimisation technique. When an objective is specified, ML algorithms learn from the data provided and use this knowledge along with the optimisation technique to achieve the desired objective (Simeone, 2018). ML algorithms can be categorised into two types of learning: supervised and unsupervised (Badillo et al., 2020). Supervised learning involves training labelled datasets to predict the nature of new inputs based on a certain objective (Simeone, 2018). Examples of supervised learning algorithms include decision tree (DT) algorithms, regression techniques, and Naïve Bayes algorithms (Badillo et al., 2020). Unsupervised learning handles problems that require clustering techniques. Examples of unsupervised learning algorithms include k-means clustering, and hierarchical clustering (Badillo et al., 2020). ML algorithms such as, linear regression, and random forest regression have been used along with BI tools by organisations, for sales forecasting, trend analysis, and non-linear data analysis, producing more accurate results with larger datasets (Tamang et al., 2021).

2.3 Deep learning models

DL models are a subset of ML algorithms based off neural networks. They can learn from vast amounts of data; providing major improvements in natural language processing and object recognition (Young et al., 2018; Zhao et al., 2019). Neural networks consist of a collection of interconnected nodes that process information similarly to humans. Each node has an input, hidden, and output layer (Kaur & Mohta, 2019). The three common types of neural networks are multilayer perceptrons (MLPs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Multilayer perceptrons are more efficient for sentiment analysis than ML algorithms (Livingston & Jenifer, 2019). Convolutional neural networks are mainly used for image classification due to their automatic learning of domain-specific features (Zargar, 2021). Recurrent neural networks like the long short-term memory (LSTM) have ushered in a major improvement over the n-gram model for language processing (Tekir et al., 2020).

DL models pose great benefits to banks in customer retention and satisfaction. For example, recurrent neural networks have been used to analyse consumer data, to determine what products or items customers would like to buy. This enables informed decision-making in terms of which products to promote, to boost sales and maintain good customer relationships (Desai et al., 2021).

2.4 Steps involved in customer data analysis using AI technologies

AI technologies are used by organisations to analyse customer data for customer satisfaction and retention (Desai et al., 2021; Kanan et al., 2023). The analysis of customer data usually involves four major steps: data collection, data preprocessing, model building, and evaluation (Desai et al., 2021; Hassanien et al., 2023; Kanan et al., 2023; Nwanakwaugwu et al., 2023).

Data collection: Data collection is the first step in the customer data analysis process. Customer data are usually in structured or unstructured formats. These data can consist of customer reviews, customer purchase history, customer demographics, and customer banking app usage (Desai et al., 2021; Kanan et al., 2023).

Data preprocessing: The data preprocessing stage focuses on transforming the raw customer data into a final analysable version. Data preprocessing steps are similar for different kinds of analysis such as sentiment analysis or data mining, with slight variations depending on the dataset and the type of analysis to be performed. Data preprocessing involves the removal of null or missing values, normalisation, splitting longer sentences into smaller units (tokenisation), removing punctuations, feature selection and stemming (Desai et al., 2021; Kanan et al., 2023).

Building the required models and evaluation: This stage involves training the existing dataset with various ML or DL models. Each model is tested by feeding it with a test dataset, and the results are compared to see which model combination or model provides the best accuracy for the required result of the customer data analysis. Various ML algorithms and DL models are suitable for different types of analysis and provide varying accuracies when evaluated (Hassanien et al., 2023; Kanan et al., 2023; Nwanakwaugwu et al., 2023).

The outcome of customer data analysis can be the prediction of customer behaviour patterns for retention and satisfaction or for targeted advertising and marketing. It can also be the prediction of churners and non-churners in the banking industry (Desai et al., 2021; Kanan et al., 2023; Hassanien et al., 2023; Nwanakwaugwu et al., 2023). Figure 2-1 depicts the customer data analysis process.

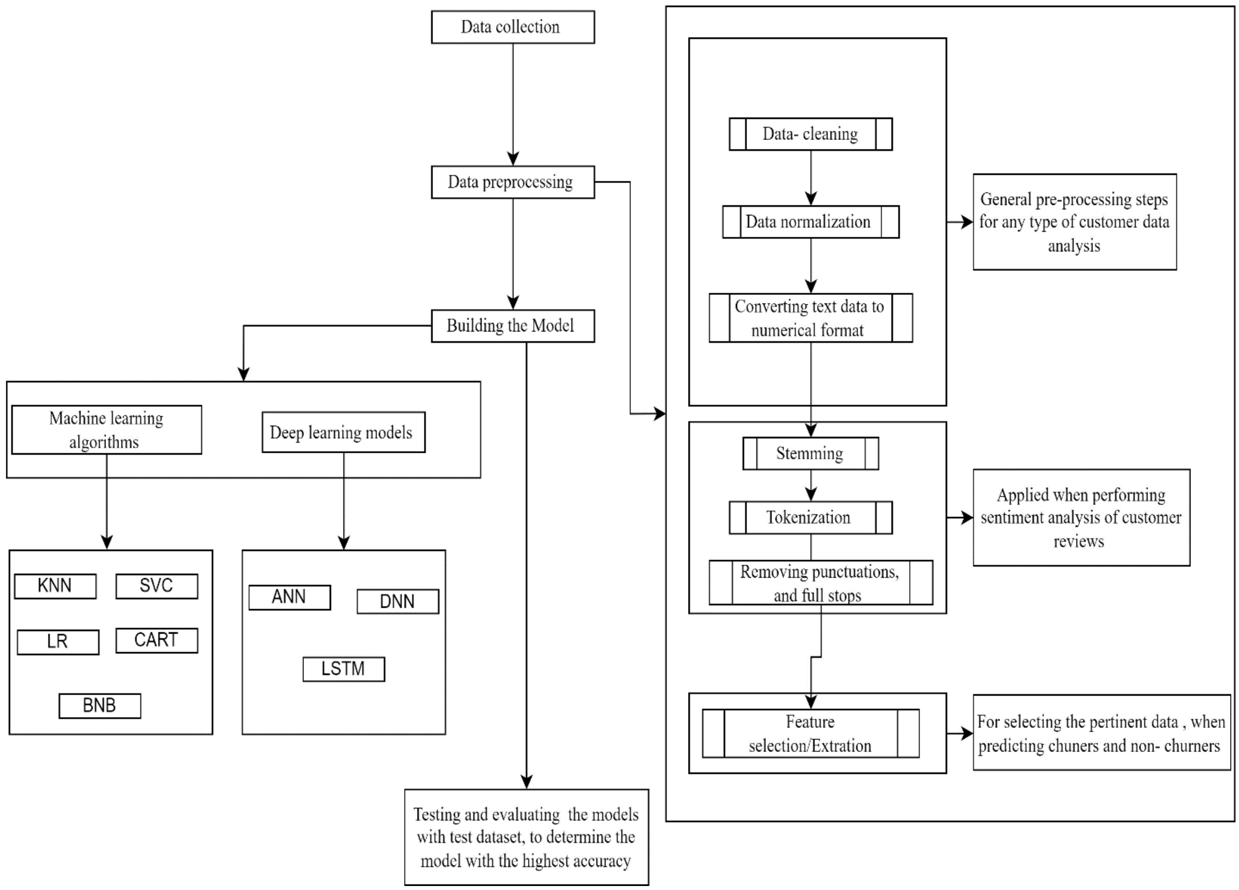


Figure 2-1: Customer data analysis process (constructed using elements from Desai et al., 2021; Kanan et al., 2023)

2.5 Drawbacks of AI technologies

AI technologies have certain drawbacks:

- DL models and ML algorithms can be challenging to implement if there is a lack of technically skilled personnel, and the results of DL models can also be ambiguous and hard to interpret (Alsheibani et al., 2018; Benbya et al., 2020).
- It can also be challenging to pinpoint accountability and transparency in AI technologies, as they are not easy to comprehend and some of their functions are invisible to humans (Siau & Wang, 2018; Vakkuri et al., 2020).
- Some AI technologies lack transparency due to the challenge of interpreting their results. This lack of transparency can lead to unethical data use (Fadlullah et al., 2017; Siau & Wang, 2018; Van Norren, 2023).

- Race and gender bias are also ethical concerns that surround AI technologies, since they are trained by humans (Siau & Wang, 2018).

Despite these drawbacks, these technologies provide the efficiency required to optimise general business processes for organisations; when applied rightly and ethically to the correct type of dataset, and for the right tasks. This use of these technologies contributes to improved customer relationships, improved sales, and increased profit margins (Durwin, 2023; Sadiq et al., 2022; Seid & Woldeyohannis, 2022).

2.6 Business intelligence

BI technologies are used to clean, import, analyse, and report data in a clean and visually appealing manner. These reports are beneficial for understanding organisational performance and identifying areas of organisational improvement (Bharadiya, 2023a). BI technologies are useful for depicting historical organisational data, current organisational progress, and charting possible future organisational trends (Zohuri & Moghaddam, 2020). Data used by BI technologies are stored in a database or warehouse. These data are imported using BI technologies and visualised using pivot tables, slicer visuals, and charts (Zohuri & Moghaddam, 2020). There are several BI technologies applicable for various kinds of analysis and visualisation. They include Tableau, Cognos, Sisense, Microsoft Power BI, Dundas BI, and Domo (Tavera et al., 2021).

BI processes are usually conducted within a BI unit or department (Krishnamoorthi & Mathew, 2018). The data professionals go through the process of data mining, data preparation, reporting, performance comparisons, descriptive analysis, prescriptive analysis, and data visualisation (Bayraktar et al., 2023). The data analysed can be structured or unstructured. Structured data fits neatly into rows and columns of tables, and includes data types such as numbers, and dates. Unstructured data does not fit into tables, due to its nature, and includes audio, video or text files (Desai et al., 2021; Kanan et al., 2023).

Data professionals in a BI department include data scientists, data analysts, business analysts, data engineers, and data quality specialists (Bharadiya, 2023a; Boina et al., 2023; Magau & Maritz, 2020; Rangineni, 2023; Skhvediani et al., 2019). Table 2-2 summarises the functions of the data professionals.

Table 2-2: Data professionals in a BI department (Bharadiya, 2023a; Boina et al., 2023; Rangineni, 2023)

Data professional	Function
Data scientists	Build and maintain AI technologies
Data analysts	Possess analytical, presentation, data modelling and reporting skills, necessary for analysing data and building dashboards
Data engineers	Ingest, process, store and transform huge amounts of data and provide an interface where data scientists and analysts can extract the data for analysis
Business analysts	Use BI tools to gain valuable insights from data and understand business requirements
Data quality specialists	Ensure optimum data quality, which is important for preventing bias and improving the prediction accuracy of ML algorithms

2.7 Business optimisation in the banking industry

Business optimisation is a process of refining procedures and tasks in an organisation to improve efficiency, financial performance, and increase profit margins (Petit, 2016). In the banking industry, the refinement of processes and procedures is geared towards customer retention and satisfaction (Hanaysha & Mehmood, 2022; Kumar et al., 2022; Nithya & Kiruthika, 2021). Banks focus on gaining knowledge about the interest of customers and what value can be provided to them. This value is provided with the combination of technological systems and individual expertise (Hanaysha & Mehmood, 2022). Examples of such technologies are BI and AI tools (Desai et al., 2021; Tamang et al., 2021).

AI and BI tools are essential for enabling long-term customer relationships (Hanaysha & Mehmood, 2022). Maintaining a good customer relationship ensures customer satisfaction and retention (Hanaysha & Mehmood, 2022). The collection, storage, and processing of customer data for improved decision-making concerning customers is essential for improving the profit margins of banks and organisations in general (Hanaysha & Mehmood, 2022). This study focused on the outcome of business optimisation. Hence business optimisation is referred to as an outcome in terms of customer retention and satisfaction.

2.8 Studies on the use of BI in organisations in Nigeria

Studies on the use of BI in Nigerian organisations have focused on banks, manufacturing companies, and telecommunications firms. These studies discussed the use of BI technologies in manufacturing companies, banks, and telecommunication firms (Achara & Eke, 2022; Hamza, 2019; Nithya & Kiruthika, 2021). A summary of the studies presented in this section is shown in Table 2-3.

Table 2-3: Summary of studies on the use of BI technologies in Nigerian organisations

Authors	Objective of the study	Theoretical models used	Findings
Nithya and Kiruthika (2021)	Highlighted benefits of BI technologies to Nigerian banks	None	Highlighted benefits were increased efficiency, provision of better customer service, and maintaining competitive advantage
Hamza (2019)	Investigated the impact of BI on Nestle manufacturing company	Diffusion of innovation (DOI) and social exchange theory (SET)	BI tools and process had a positive overall impact on the organisational values of Nestle Manufacturing company
Achara and Eke (2022)	Examined the impact of BI on the service delivery performance of four major telecommunication firms in Port Harcourt, Nigeria	SERVQUAL MODEL	The use of BI technologies in the telecommunications companies led customer satisfaction

Nithya and Kiruthika (2021) highlighted the benefits gained by Nigerian banks due to the implementation of BI technologies. The benefits highlighted were increased efficiency, provision of improved customer service, and maintaining competitive advantage. They also stated that the adoption of BI technologies by Nigerian banks promoted the adoption and use of e-banking services such as digital banking and real-time customer support interactions. These features helped to ease the minds of customers and ensure that their needs could be met from the comfort of their homes.

Hamza (2019) investigated the impact of BI on Nestle, a manufacturing company located in Abuja, Nigeria. First, the study noted that the BI processes varied depending on the type of organisation, the structure of the organisation, and the goals of the organisation. Second, the study showed that the use of BI processes and tools allowed Nestle manufacturing to maintain and manage relationships, with its suppliers, thus improving and increasing the speed of operations, service delivery, and procurement activities. Third, the use of BI technologies produced an evident improvement in customer service delivery. The BI technologies in use by Nestle enabled the analysis of customer feedback quickly and efficiently. The technologies also provided an avenue for customers and suppliers to make queries from the comfort of their homes. Lastly, the use of BI technologies provided Nestle with real-time updates on their prices and customer service quality. Therefore, the study concluded that the use of BI tools and processes had a positive overall impact on the organisational value of Nestle manufacturing company.

Achara and Eke (2022) examined the impact of BI on the service delivery performance of four major telecommunication firms in Port Harcourt, Nigeria. The telecommunication firms were Airtel, Mobile telephone network (MTN), Globacom, and 9mobile. The results of their study showed that BI had a transformational and positive impact on the performance of telecommunication firms. BI allowed key decision making in real time and ensured optimal use of resources. They concluded that with the use of BI technologies, telecommunications companies could provide customer satisfaction by providing high-quality services to customers. They also recommended that telecommunication companies have well-defined business goals, adequate company records, and invest in data quality, as these were the requirements to derive the full benefits of BI technologies.

The studies reviewed show that the telecommunications, and banking industry in Nigeria have implemented BI technologies. These studies also show that there is a considerable level of awareness and use of BI technologies in Nigerian organisations.

2.9 Studies on the use of AI in organisations in Nigeria

Studies on the use of AI technologies in Nigerian organisations have focused on the benefits of its usage in the telecommunication, banking and healthcare industry. Studies have also noted its infancy within SMEs, its novelty in the healthcare industry, its growing awareness in journalism, and its potential to combat insecurity in Nigeria (Abdulsalam et al., 2022; Borokini et al., 2023; Ekpa et al., 2023; Okoliko et al., 2023; Okwor, 2022; Orji et al., 2021; Owoyemi et al., 2023; Udoh et al., 2022; Ukpong, 2022). This section highlights studies that have discussed the use of AI in banks, telecommunications firms, the healthcare industry, and SMEs in Nigeria. A summary of studies on the use of AI technologies in Nigerian organisations is shown in Table 2-4.

Table 2-4: Summary of studies on the use of AI technologies in Nigerian organisations

Authors	Objective of the study	Findings
Ukpong (2022)	Examined the integration of AI technologies for the innovation of financial processes by commercial banks in Nigeria	Confirmed that the AI technologies could be used in commercial banks to improve customer service and for credit scoring.
Okoliko et al. (2023)	Examined the impact of AI on deposit money banks in Nigeria	The use of AI technologies in deposit money banks, significantly improved the efficiency of the banks
Ekpa et al. (2023)	Noted that the deployment of automated chatbot banking services in deposit money banks	The deployment of chatbots positively impacted the performance of the banks
Borokini et al. (2023)	Noted the use of chatbots by commercial banks in Nigeria to improve customer experience	Banks used chatbots to provide a multitude of personalised services to customers
Busayo et al. (2023)	Investigated the impact of AI on the quality of service provided by MTN	The use of AI technologies by MTN had an overall positive impact on the quality of service provided to their customers
Abdulsalam et al. (2022)	Discussed the use of Relief-F CART and ANNs for predicting customer churn in the Nigerian telecommunications industry	The combination of Relief F for feature selection and ANN for classification was more efficient for predicting customer churn

Orji et al. (2022)	Suggested the use of BNB, SVC, and LR algorithms for sentiment analysis of Twitter comments to enhance marketing strategies for SMEs	Informed SMEs in Nigeria about the opportunities and benefits of using AI techniques, especially for analysing social media data
Owoyemi et al. (2023)	Developed a recommendation system for the suggestion of healthcare plans and services to healthcare clients in Nigeria	The model built using the k-nearest neighbour and cosine similarity, was evaluated and deployed via an application programming interface (API)

Ukpong (2022) examined the integration of AI technologies for the innovation of financial processes by commercial banks in Nigeria. Ukpong (2022) identified ten ways to integrate AI technologies for the personalised banking experience of customers. These included customer support, image recognition, speech recognition, chatbots, natural language processing, sentiment analysis, virtual financial assistance, personal planning, personalised reminders, and automated transactions. The study results showed a high rating for all AI integration modes and confirmed the conclusion that AI technologies could be used in commercial banks to improve customer service and for credit scoring.

Okoliko et al. (2023) examined the impact of AI on deposit money banks in Nigeria. The study showed that the use of AI technologies in deposit money banks significantly improved the efficiency of the banks. The introduction of e-banking platforms, with AI capabilities, led to massive changes in service delivery techniques, and the range of products offered by the banks. Okoliko et al. (2023) noted that e-banking services enabled customers to make transactions from the comfort of their homes and make queries without appearing physically at the bank. This led to an improvement in customer relationships. Okoliko et al. (2023) further recommended that these banks implement AI-powered chatbots and virtual assistants to provide personalised recommendations to customers and assist with basic transactions to improve customer relationships further.

Ekpa et al. (2023) noted that the deployment of automated chatbot banking services in deposit money banks in Nigeria positively impacted the performance of the banks. Chatbots were used to answer customer questions and provide services like bill payment, and funds transfers. The integration of machine learning and natural language processing enabled chatbots to provide round-the-clock services to customers.

Borokini et al. (2023) noted the use of chatbots by commercial banks in Nigeria to improve customer experience. The first commercial bank in Nigeria to implement the chatbot was the United Bank for Africa (UBA) in 2018. Chatbots provided a multitude of services to customers, ranging from the ability to purchase airtime, make complaints, and connect to customer care agents seamlessly. This meant that customers did not have to physically go to the bank and could perform a variety of bank transactions from the comfort of their homes. Borokini et al. (2023) also stated that 10 other commercial banks in Nigeria had implemented chatbots, to create an improved personalised banking experience for their customers. Table 2-5 shows the list of banks along with the names of the chatbots.

Table 2-5: List of Nigerian commercial banks and their chatbot names (Borokini et al., 2023)

Bank Name	**Chatbot**
Zenith Bank	ZIVA – abbreviation for Zenith Intelligence virtual assistant
United Bank for Africa	Leo – a typical male name
Fidelity Bank	Ivy - typical female name
Ecobank	Rafiki – means friend in Swahili
Access Bank	Tamada – a combination of the words “Tamara” meaning date in Hebrew and “Ada” an Igbo female name
Heritage Bank	No name
Keystone Bank	Oxygen – a colourless and odourless gas
Stanbic IBTC	Sami – an abbreviation of a typical male or female name
First City Monument Bank	Temi- an abbreviation for the Yoruba name Temiloluwa or Temitope
Sterling Bank	Kiki – a typical female name

Busayo et al. (2023) investigated the impact of AI on the quality of service provided by MTN. The study focused specifically on three AI technologies: data mining, ML, and chatbots. The study noted that the quality and nature of the service provided to customers by MTN was an essential part of the journey to improve the customer experience. Hence, the incorporation of ML, data mining, and chatbots was paramount to ensuring the analysis, support, and understanding of customer queries, reviews, and behavioural patterns. The results of the study revealed that data mining and chatbots, when utilised by MTN staff, produced a positive impact, causing an improvement in customer satisfaction and loyalty. ML techniques also helped highlight top-quality customers and reduced human error. Busayo et al. (2023) therefore concluded that the use of AI technologies by MTN had an overall positive impact on the quality of service provided to their customers.

Abdulsalam et al. (2022) discussed the use of Classification and Regression trees (CART) and artificial neural networks (ANNs) for predicting customer churn in the Nigerian telecommunications industry. The model consisted of the combination of the Relief-F feature selection technique along with the CART and ANN. The purpose of the model was to identify telecom subscribers who were most likely to leave and those who were most likely to stay. The model relied on datasets such as customer care call data, as well as other descriptive information about customers held by the telecom service provider. Data mining and feature selection were performed using Relief-F, and classification was performed with CART and ANN, with the results captured in the matrix laboratory software (MATLAB). After the evaluation and deployment of the model, Abdulsalam et al. (2022) concluded that the combination of Relief F for feature selection and ANN for classification was more efficient and provided a higher precision rate than the combination of Relief-F and CART. They therefore concluded that this combination was a more suitable model for the prediction of customer churn in the telecommunications industry in Nigeria.

Orji et al. (2022) suggested a novel approach to enhance marketing strategies in BI for SMEs. This approach used Bernoulli Naïve Bayes (BNB), linear support vector classifier (SVC), and logistic regression (LR) algorithms for sentiment analysis of Twitter comments. Orji et al. (2022) aimed to use this novel approach to inform SMEs in Nigeria about the power of social media analytics and how they could use these models to improve their productivity and efficiency. In conclusion, Orji et al. (2022) suggested that SMEs could adopt these techniques for improved business processes. The study, therefore, informed SMEs in Nigeria about the opportunities and benefits of using AI techniques, especially for analysing social media data.

Owoyemi et al. (2023) developed a recommendation system for the suggestion of healthcare plans and services to healthcare clients in Nigeria. The model is the first application of a recommendation system in the Nigerian health care sector. Owoyemi et al. (2023) used a content-based methodology for the recommendation system. The system was built using k-nearest neighbour (KNN) and cosine similarity for filtering and recommendation of healthcare plans based on user-selected preferences. The building process involved collecting health care plans, their characteristics and their ratings from various health management organisations in Nigeria. The collected data was cleaned, and a model was developed using KNN and cosine similarity. The model was then evaluated and deployed via an application programming interface (API).

The studies reviewed show the banking industry in Nigeria as frequent utilisers of AI technologies. The studies also show that the healthcare industry and telecommunications firms in Nigeria use AI technologies. The studies further show the infancy of AI within SMEs. Most of the research on AI within Nigeria focuses on the potential use of AI in Nigeria, with the banking and telecommunications industry notable for using AI technologies.

2.10 AI technologies used by banks in other countries

Banks in other countries have used ML algorithms to enhance customer experience. Chatbots, virtual assistants, and data mining techniques have all been used to ensure customer satisfaction and retention, leading to an increase in revenue (Bharadiya, 2023b). Customers are essential to the survival of any business, and the same can be said for the banking industry. Retaining current customers and attracting new ones is the major goal of any financial institution (Durwin, 2023; Hassanien et al., 2023; Sadiq et al., 2022; Seid & Woldeyohannis, 2022).

In Ethiopia, commercial banks use models such as LR, support vector machine (SVM), KNNs and deep neural networks (DNNs) to predict churners and non-churners. Churners are customers who are likely to leave the bank, while non-churners are customers who are likely to stay (Seid & Woldeyohannis, 2022). Due to the growing number of customers who switch from their banks to other competitor banks, customer retention has taken more precedence over customer acquisition. Banks around the world focus more on satisfying and retaining existing customers, before targeting new customers (Durwin, 2023; Haddadi et al., 2022; Sadiq et al., 2022; Seid & Woldeyohannis, 2022).

In India, the use of AI technologies in the banking industry has increased, leading to improvements in customer service and overall business processes. The deployment of AI-powered chatbots and virtual assistants provides 24-hour real-time support to customers. The use of various personalised banking services is made available with the help of data-oriented analysis to retain and satisfy customers (Durwin, 2023). Natural language processors (NLPs) have also been used for analysis of customer sentiment and feedback, providing beneficial insight into what customers want, to help bank managers make more informed decisions (Durwin, 2023). The Bank of India and the Industrial Credit and Investment Cooperation of India (ICICI) are the main employers of AI technologies in India. These banks have utilised these techniques to improve their overall banking services and enhance their customer experiences (Durwin, 2023).

In Iran, the loss of existing customers has been an extremely concerning issue. As such, the banking industry has utilised ANNs and DNNs to mitigate against this loss (Haddadi et al., 2022). Other models such as the Bi-directional long short-term memory (Bi-LSTM) have also been suggested to help examine and watch customer information over a certain period, to be able to anticipate customer behaviour in the future. ANNs offer an easy approach to accurately analysing data and can identify patterns in large datasets and learn from experience rather than programming. By using ANN for data mining, banks have been able to make considerable progress in customer retention by identifying patterns in customer data stored in data warehouses. This is beneficial for customer targeting and acquisition of new customers (Nwanakwaugwu et al., 2023).

The growing increase in size and the varying nature of customer data is the major reason for using AI technologies. With the competitive nature of banks, and every bank wanting to ensure that their customers make a lifelong commitment, the utilisation of AI technologies has become paramount, for the analysis of large customer datasets. Therefore, banks use these technologies to ensure customer engagement, contentment, and prioritisation (Haddadi et al., 2022; Hassanien et al., 2023; Sadiq et al., 2022). The list of the AI technologies presented in this section are shown in Table 2-6.

Table 2-6: AI technologies used by banks in other countries

AI algorithms	Outcome of using the algorithms	Country
• Logistic regression • Support vector machine • k-nearest neighbour • Deep neural networks	• Predicting customer churn	Ethiopia
• Chatbots • Natural language processors	• Personalised messaging • Analysis of customer sentiments for better product development	India
• Artificial neural networks • Deep neural networks • Bidirectional long short-term memory	• Preventing the loss of existing customers	Iran

2.11 Gap in the literature

Research on AI technologies in the banking industry has not explored how AI technologies are used by banks. Previous research on AI technologies in the banking industry has listed examples of the technologies that are used for customer retention and satisfaction (Durwin, 2023; Haddadi et al., 2022; Sadiq et al., 2022; Seid & Woldeyohannis, 2022). In Nigeria, most research report the potential of using AI technologies within certain organisations, with the banking and telecommunications industry being notable employers of AI techniques (Abdulsalam et al., 2022; Ukpong, 2022; Borokini et al., 2023; Busayo et al., 2023).

Research on AI technologies in the Nigerian banking industry has also not explored how AI technologies are used by commercial banks for customer retention and satisfaction. Research rather focused on the impact of AI technologies or listed the AI technologies already deployed such as the chatbots used by commercial banks (Abdulsalam et al., 2022; Borokini et al., 2023).

This research study, therefore, explores how commercial banks in Nigeria use AI technologies for customer retention and satisfaction.

2.12 Chapter summary

This chapter provided a summary of studies on the use of AI technologies in banks within and outside Nigeria. The chapter also provided a review on the use of BI technologies in Nigerian organisations. The chapter further explained the steps involved in the analysis of customer data using AI technologies, highlighted the drawbacks of AI technologies and presented the gap in literature.

Chapter 3 : Theoretical Framework

This study used the Organisational information processing (OIP) theory; viewing AI technologies as information processing capabilities that were capable of handling information processing needs of banks. In this chapter, the process of theory selection is described. The OIP theory is defined, and the constructs are explained. The chapter also reviews studies that have used the theory. Lastly, the applicability of the theory to the research study is stated, and justification for selecting the theory is given.

3.1 Theory selection

This study focused on the use of AI technologies in Nigerian commercial banks. This study neither focused on the adoption issues nor the perceptions of AI technologies by customers or managers. Hence frameworks like the Technology acceptance model (TAM) and Diffusion of innovation (DOI) theory were not suitable theoretical lenses for the study. The OIP theory, however, proved suitable for this study. The theory enabled the exploration of AI technologies as information processing capabilities that could be utilised to achieve customer retention and satisfaction in the banking industry.

Previous studies that explored the benefits of using AI technologies in various organisations in Nigeria, employed the TAM and DOI theoretical models (Busayo et al., 2023; Udoh et al., 2022). While studies on the use of AI in Nigerian banks, noted the benefits of AI technologies, without using any theoretical framework (Borokini et al., 2023; Ekpa et al., 2023; Ukpong, 2022). The TAM and DOI frameworks have been used extensively for exploring adoption of AI technologies in organisations (Alsheibani et al., 2018; Alsheibani et al., 2020; Tripathi et al., 2020). These frameworks have also been used for exploring human perceptions of AI technologies, along with the benefits and outcomes of using such technologies, all of which have been documented in literature (Alsheibani et al., 2018; Alsheibani et al., 2019; Alsheibani et al., 2020; Radhakrishnan & Chattopadhyay, 2020; Tripathi et al., 2020). What has scarcely been documented, however, is how organisations use AI technologies.

Since this study intended to explore how AI technologies were used by commercial banks in Nigeria, the study had to adopt a suitable theoretical framework. AI technologies can be seen to improve the information processing capabilities of an organisation, by analysing large amounts of data for business optimisation (Shrestha et al., 2021).

The OIP theory was suitable for exploring how commercial banks in Nigeria use AI technologies. This theory adequately captured the growth of customer data and the needs of customers as information processing needs. The theory also captured AI technologies as information processing capabilities, and customer retention and satisfaction as performance.

Theories such as the soft systems methodology and the task-technology fit theory have also been used in information systems research, to explore the use of technologies within various organisations (Damenu & Beaumont, 2017; Sharma et al., 2020; Rahi et al., 2021). The soft systems methodology is a problem-solving approach that aims to improve a problematic situation in a system. The task-technology fit theory can be used to explore the fit between technology capabilities and tasks, and its implications on individual performance (Damenu & Beaumont, 2017; Rahi et al., 2021).

This research did not use the soft systems methodology or the task- technology fit theory, because it intended to provide knowledge on how AI technologies were used in commercial banks. This was achieved by viewing AI technologies as information processing capabilities used to match the information processing needs of commercial banks. Hence the OIP theory was a good fit for this study.

3.2 The Organisational Information Processing theory

The Organisational information processing theory was founded by Galbraith (Galbraith, 1974). The theory examines how information processing capabilities can be used to match information processing needs in an organisation for optimal performance. The major goal of the theory is to match the information processing capabilities of an organisation to its information processing needs for optimal performance. Organisations require adequate information processing capabilities to cope with uncertainties in the business environment (Premkumar et al., 2005). These uncertainties may be due to the complex nature of business environments, the constant growth of data, and the dynamic nature of markets (Tavera et al., 2021).

3.3 Constructs of the OIP theory

The OIP theory contains three major constructs: information processing needs, information processing capabilities, and the fit between the two to obtain optimal performance. These constructs are explained in this section.

Information processing needs: Information processing needs arise from uncertainties in a business environment (Premkumar et al., 2005). These uncertainties can be classified into various forms such as task uncertainty, partnership uncertainty, and environmental uncertainty (Premkumar et al., 2005). Environmental uncertainties are factors that influence information processing needs. Partnership uncertainty arises from an organisation's perceived uncertainty about its partner's behaviour; and task uncertainty arises from the attributes of tasks in various procurement activities (Premkumar et al., 2005).

Environmental uncertainty was considered for this study. Task uncertainty was not considered, because the study focused on the use of AI technologies for tasks, for which they were applicable. There was, therefore, no uncertainty in the task. Partnership uncertainty was also not considered, because the study focused on Nigerian commercial banks, and did not consider the banks' relationship with other organisations. In the banking industry, a major environmental uncertainty is the constant growth of customer data and the needs of customers (Sadiq et al., 2022; Tavera et al., 2021; Zohuri & Moghaddam, 2020). These needs may push banks to use certain AI technologies for efficient analysis, leading to the business optimisation outcome of customer retention and satisfaction (Durwin, 2023; Hassanien et al., 2023; Sadiq et al., 2022). The nature of the environmental uncertainty in this study was internal and related to the performance outcome of customer satisfaction and retention. Hence external factors such as policy changes were not considered.

Information processing capabilities: Information processing capabilities can be defined as the level of information technology support that an organisation employs to match information processing needs (McCormack & Trkman, 2014). This support comprises information and communication technologies like BI tools, or AI technologies (Krauter & Mayer, 2019; Premkumar et al., 2005).

Fit: Fit primarily explores the interaction between information processing needs and information processing capabilities and the effect of their interaction on business performance. Fit explores how information processing capabilities help cater for information processing needs by analysing large amounts of data, for optimal business performance (Premkumar et al., 2005).

Performance: Performance is the outcome of matching information processing capabilities to information processing needs (Premkumar et al., 2005).

The OIP theory is depicted in Figure 3-1.

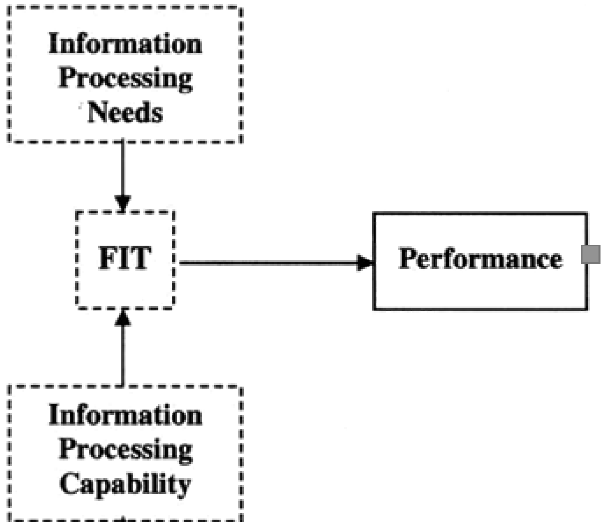


Figure 3-1: Organisational information processing theory (Premkumar et al., 2005)

3.4 Studies that have used the OIP theory

The OIP theory has been used in various information systems research, most notably in supply chain management (Busse et al., 2017; Premkumar et al., 2005). The theory has also been applied in qualitative studies to investigate the effect of organisational structure on information overload, and the effect of information processing needs on BI (Krauter & Mayer, 2019; McCormack & Trkman, 2014). A summary of the studies that have used the OIP theory is displayed in Table 3-1.

Table 3-1: Previous studies that have employed the OIP theory

Authors	Objective of the study	Findings
Premkumar et al. (2005)	Explored the fit between information processing needs and information processing capabilities in an inter-organisational supply chain context, and its effect on performance	The interaction between information processing needs and capabilities significantly affect performance
Busse et al. (2017)	Explored how information processing needs could be managed, from the context of sustainability in supply chain management	A proper understanding of what occurs in a complex supply chain would promote sustainable supply chain management
Krauter and Mayer (2019)	Investigated the role of organisational structure in information overload	Information overload occurs when Information Processing requirements outweigh Information Processing Capacities. Organisational structure should be chosen to enable successful task execution, and mitigate information overload
McCormack and Trkman (2014)	Focused on the role of information processing needs in the continuous use of business intelligence and the factors that influence those needs	Technology enabled business intelligence drastically enhances information processing capabilities, but does not have the same effect on information processing needs

Premkumar et al. (2005) used the OIP theory to explore the fit between information processing needs and information processing capabilities in an inter-organisational supply chain context, and its effect on performance. Premkumar et al. (2005) highlighted information processing needs as characteristics of the product and procurement environment. Information processing capabilities were identified as the level of information technology support for activities in the procurement life cycle. Premkumar et al. (2005) concluded that the interaction between information processing needs and capabilities significantly affected performance.

Busse et al. (2017) employed the OIP theory to explore how information processing needs could be managed, from the context of sustainability in supply chain management. Busse et al. (2017) identified task uncertainty, source uncertainty, and supply chain uncertainty as sustainability-related uncertainties; and showed the extent to which these uncertainties translated into information processing needs. Busse et al. (2017) concluded that a proper understanding of what occurs in a complex supply chain would promote sustainable supply chain management.

The studies reviewed show that information processing needs can be viewed as either task uncertainty, partnership uncertainty, or environmental uncertainty. Information processing capabilities are information and communication technologies that organisations employ. Fit is the process of matching information processing capabilities to information processing needs.

3.5 Applicability of the OIP theory to the research study

The constructs of this theory were placed into a specific context; to serve the purpose of the study.

Information processing needs: This research focused on environmental uncertainties, and highlighted the growth of customer data, and the needs of customers as information processing needs in the banks (Durwin, 2023; Hassanien et al., 2023; Sadiq et al., 2022). These needs motivated the banks to utilise AI technologies. The nature of the environmental uncertainty in this study was internal and related to the performance outcome of customer satisfaction and retention. Hence external factors such as policy changes were not considered.

Information processing capabilities: These were the AI technologies used by the banks to meet information processing needs (growth of customer data and needs of customers).

Fit: in this study, Fit explored how the information processing capabilities were used to match the information processing needs, to achieve optimal performance (customer retention and satisfaction).

Performance: Performance was referred to as the outcome of business optimisation, which for this study was customer retention and satisfaction.

Figure 3-2 illustrates the OIP theory as it relates to this research.

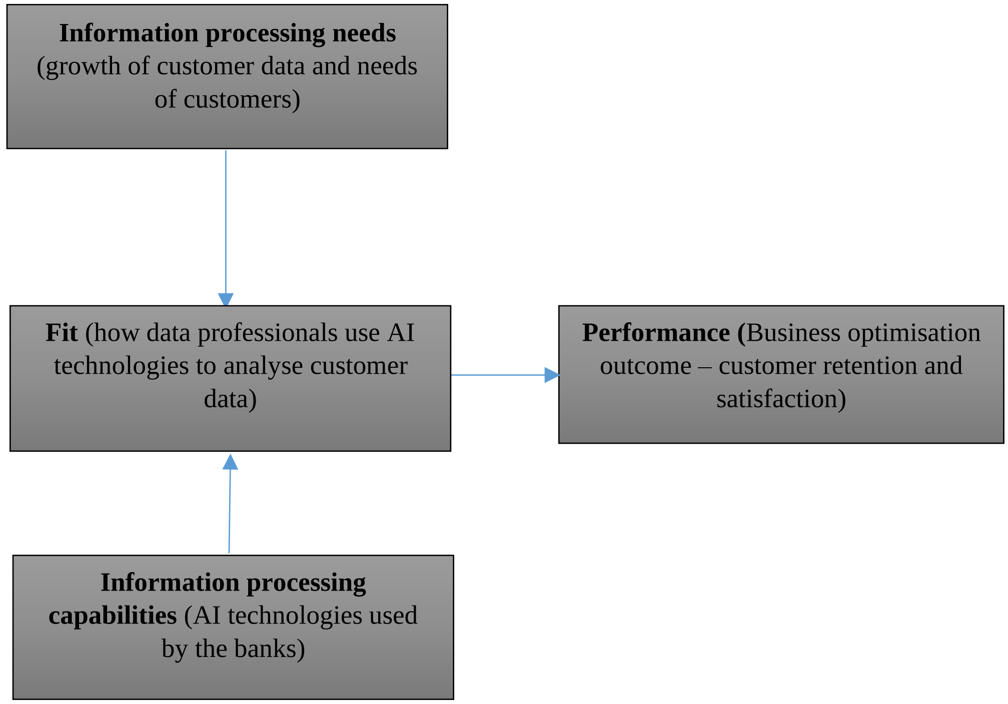


Figure 3-2: Applicability of the OIP theory to this research study

3.6 Limitations of the OIP theory

The OIP theory, though suitable for this research, is not without limitations. The OIP theory fails to consider how organisations can change over time, in areas such as downsizing, and outsourcing technological projects (Bouchrika, 2024). The OIP theory also fails to address organisational hierarchy, and conflicts that may arise due to such hierarchy in an organisation (Bouchrika, 2024). Regardless of these limitations, the OIP theory is applicable in fields such as business and artificial intelligence, and for understanding organisational behaviour, and contributes to the development of new ideas or models in these areas (Bouchrika, 2024; McCormack & Trkman, 2014). The OIP theory was suitable for this research, because of the focus on the use of AI technologies in Nigerian commercial banks for business optimisation. The limitations of the OIP theory, did not also hinder the research, as factors such as organisational culture, policies and external environmental uncertainty were not part of the scope of the research.

3.7 Chapter summary

This chapter introduced the OIP theory as the theoretical framework used in this study. The chapter explained the constructs of the OIP theory and provided information on the use of the theory by previous studies. The chapter further justified the selection of the OIP theory and depicted the applicability of the theory to the research study.

Chapter 4 : Research Methodology and Design

This chapter provides the research methodology employed in this study. The chapter begins by addressing the research method used in this study and discussing the research philosophy. The chapter describes the methodological processes used in the study. The chapter also provides data collection approach, research instrument, sampling technique, data analysis method, methods for ensuring the reliability and validity of the research study, and ethical considerations.

4.1 Research methods used for the study

This research used qualitative research methods. This approach was ideal since the study aimed to provide knowledge of how Nigerian commercial banks used AI technologies. This knowledge was gained by interacting with data professionals in the business intelligence department of commercial banks. The qualitative research method provides researchers with knowledge about a topic through the experience of participating in the environment under study (Mohajan, 2018). Hence this method was appropriate for this study.

4.2 Philosophical paradigm

This study took an interpretivist stance. An interpretivist approach focuses on a deep understanding of a particular phenomenon and considers the knowledge of the subject to be of great importance for the understanding of the phenomenon (Al-Ababneh, 2020). This study also employed a relativist ontology and a constructivist epistemology (Adom et al., 2016; Moon & Blackman, 2014). This study took the ontological position that reality is constantly constructed in the human mind, based on lived experiences, and identified social actors as custodians of reality (Kamal, 2019; Rashid et al., 2019). Hence, experts and professionals in the BI departments of banks were seen as actors who had knowledge about the use of AI technologies for customer retention and satisfaction. This study also employed a constructivist epistemology. Therefore, knowledge about the use of AI technologies was obtained by interacting with the data professionals in the BI departments of banks (Al-Ababneh, 2020). This was done to understand how they used these technologies.

4.3 Research approach

This research employed an abductive approach. It used the OIP theory, as a theoretical framework to explore the use of AI technologies in Nigerian commercial banks. Hence, during data analysis, a combination of the deductive and inductive approach was used. This study employed deductive reasoning, which provided insight on concepts pertinent to the study, and inductive reasoning to verify the applicability of the theory to the research study (Earl Rinehart, 2021; Johnson et al., 2020; Rashid et al., 2019). Table 4-1 shows the research flow for this study.

Table 4-1: Research flow (Informed by Saunders' research onion (Seuring et al., 2021)

Research Philosophy	Relativist ontology Constructivist epistemology Interpretivist paradigm
Research Approach	Abductive
Methodological Choice	Qualitative
Research Strategy	Case study
Time Horizon	Cross-sectional
Data collection method	Semi-structured interview questionnaires
Unit of analysis	Bank
Data analysis method	Thematic analysis

4.4 Research design

This study was interpretivist, abductive, and followed a qualitative approach deploying a multiple case study design. This research was exploratory as it aimed to explore how commercial banks in Nigeria used AI technologies for customer retention and satisfaction. This was done by engaging with data professionals in the BI department of banks (Mohajan, 2018).

4.5 The multiple case study design

This explorative study used a multiple case study design. Multiple cases were selected to provide similar results to strengthen the generalisability of the findings and provide a more compelling proof of validity. The decision to use a multiple case study design for this research was based on three reasons:

- Case studies are naturally exploratory and aid the investigation of a phenomenon, using qualitative methods (Rashid et al., 2019). This exploratory approach suited this study well, as it aimed to explore how data professionals in the BI departments of Nigerian commercial banks used AI technologies.

- Case studies explore a phenomenon that is underexplored (Gammelgaard, 2017). There is dearth of literature, on how AI technologies is used in the Nigerian banking industry. Therefore, the use of these technologies in the banking industry is a phenomenon that has been underexplored in Nigeria.
- Multiple case studies have been suggested to be more appropriate for improving the quality and rigor of qualitative studies. The findings from multiple cases provide a more compelling proof of validity (Yin, 2009).

4.5.1 Case selection criteria

This study used a multiple case study design, consisting of three cases. Three banks were selected from 19 commercial banks in Nigeria. The adequacy of cases was determined by following the literal replication logic for multiple case study selection, and the appropriateness of cases was determined using the criterion sampling selection strategy (Shakir, 2002). The banks were selected based on a criterion which ensured that they provided the required information for this study. The case selection criteria are shown in Table 4-2

Table 4-2: Case selection criteria

Criteria	Details
Department	The banks should have an analytics department or BI department
Technology	The analytics department should be conversant with using deep learning models and or machine learning algorithms.
Access	The commercial bank should be willing to give access to interview their data professionals in the BI department

There are two replication logics for selecting multiple case studies (Shakir, 2002; Yin, 2009):

1. *Literal replication:* selection of cases to predict similar results.
2. *Theoretical replication:* selection of cases to produce contrasting results or to increase the degree of certainty when opposing theories have slight differences.

To meet the adequacy of cases in a multiple-case study design, the replication logic suggests between three to four cases for literal replication, and six to eight for theoretical replication (Shakir, 2002). To meet the appropriateness of multiple case studies, a sampling strategy must be selected (Shakir, 2002).

4.5.2 Case selection process

Out of the 19 banks, 12 commercial banks were contacted for this research. The study opted for 12 due to time constrains. The researcher sent E-Mails, and LinkedIn messages to the head of the BI department in each of the banks. The messages gave a brief background of the study, the research instrument, and inquired if they were willing to grant access to their BI department. Out of the 12 banks:

- Four banks did not respond to the inquiries sent.
- Two banks noted that their major analytical processes were handled from head offices located in a different African country.
- Two other banks declined to participate in the interview process due to privacy concerns.
- Four banks were left.

The heads of the BI department in each of the four banks, agreed for their staff to be interviewed. However, one bank out of the four banks did not use AI technologies and had no intention of employing AI soon. This left three remaining banks. Per the assurance of anonymity provided to the banks, their names were not disclosed in this research. For reference purposes, they were given pseudonyms: Bank A, Bank B, and Bank C.

4.6 Time frame

This study used a cross-sectional time frame due to time constraints and the exploratory nature of the study. It aimed to explore the use of AI technologies in Nigerian commercial banks over a given period.

4.7 Data collection

Data was collected using semi-structured interview questionnaires. A total of 20 respondents were interviewed across the three banks: six respondents in Bank A, and seven respondents each in Banks B and C (see Appendix F for respondents' profile). The data collection process began in November 2023 and ended in the first week of December 2023. The interview sessions were recorded with the consent and permission of the respondents and transcription was done thereafter. There was no need for translation during the interview process; because English is the official language spoken in Nigeria (Oloruntoba & Pinxteren, 2023).

4.7.1 Participant sampling and target population

The target population for this study consisted of data professionals in the BI department of banks. These professionals were data analysts, data scientists, and data engineers. This study used purposive sampling to select the most experienced data professionals in the selected banks (Palinkas et al., 2015). Participants were evaluated based on age, years of experience, current role, and years of working in the bank. This was done to ensure that the selected participants were knowledgeable and experienced enough to provide information related to the study. Tables 4-3 summarises the profile of the respondents.

Table 4-3: Respondents summary

Roles of Respondents Interviewed	**Number of Respondents in the Role**	**Range of Career Experience per Role (Years)**	**Age range per Role (Years)**
Data analyst	4	3-12	28-42
Data scientist	11	2-7	21-36
Data engineer	3	2-6	28-35
BI analyst	1	5	25-30
Data quality and governance specialist	1	4	31

4.7.2 Unit of analysis

The unit of analysis for this study was the bank, which had a BI department. This department was suitable for providing the information required in this research. Previous studies have shown that BI departments consist of data professionals who interact with BI and AI technologies daily (Krishnamoorthi & Mathew, 2018; Shollo & Galliers, 2016). A BI department consists of data analysts, data engineers, and data scientists. These professionals perform tasks such as data mining, data preparation, reporting, performance comparisons, descriptive analysis, prescriptive analysis, and data visualisation (Feldman & Himmelstein, 2013).

4.7.3 Research instrument design

This study used semi-structured interviews to allow respondents adequately express themselves and state their experience with the use of AI technologies in the BI department (See Appendix E for Research instrument). The questions were developed following the guidelines of Kallio et al. (2016), Turner (2010) and Qu and Dumay (2011) for question development in semi-structured interviews. Semi-structured interviews are flexible, which enables a researcher to dive into new areas to obtain rich information.

A pilot test was conducted to determine the appropriateness of the questions (see Appendix G for pilot test results). After the pilot test, appropriate changes were made to the questions to ensure that they would elicit the required responses from the respondents.

The interview process began with an introduction to gain familiarity with the interviewee. The introductory section of the interview collected details such as age, occupation, and years of work experience from the respondents. The rest of the interview questionnaire had three sections:

a) Information processing needs: This section consisted of questions on customer needs and the data types handled by the department.
b) Information processing capabilities: This section consisted of questions on the AI technologies, resources, and skillsets needed to perform the predictive and descriptive analysis needed for customer retention and satisfaction.
c) Fit: This section covered questions on how data professionals in the BI department used AI technologies for data analysis tasks.

16 interviews were conducted face-to-face, while four were conducted virtually. Four interviews were conducted virtually, because some of the participants were unavailable for the scheduled face-to-face interview time slot. Each interview lasted between 25-40 minutes

4.7.4 Data saturation point

The data saturation point for this study was reached whilst interviewing participants in the third bank. At this stage, no new themes related to the types of BI technologies used, AI technologies used, and the tasks for which they were used for emerged. At the point of saturation, 15 individuals had been interviewed, and certain points were identified as reoccurring and therefore termed as 'true', in line with the data triangulation process. These points were re-iterated by several data professionals in the various banks (Guion et al., 2011). After saturation had been achieved, five more interviews were conducted, to further confirm the saturation process (Saunders et al., 2018).

Saturation is a process that is widely applied in qualitative research, predominantly in the data collection or data analysis phases, to improve the overall quality of research (Mandal, 2018; Saunders et al., 2018; Tight, 2023). Saturation has been used to provide an indicator for the quality of qualitative research and to match quality measurements in quantitative research (Mandal, 2018; Saunders et al., 2018; Tight, 2023).

For this study, saturation was considered in terms of data saturation and was achieved during the data collection process. Some of the notes drawn from the data collection process at the point of saturation are:

- The datasets analysed by the banks consisted primarily of structured datasets, in the form of occupational, demographic, and transactional customer data.
- Technologies such as Microsoft Power BI, Microsoft Azure, and Oracle were popular tools for data visualisation, data integration, and data storage.
- ML algorithms were used the most, frequently for customer data analysis tasks. DL models were not used.

4.8 Data analysis method

This study employed thematic analysis as the data analysis method. Thematic analysis was used to categorise, understand, and classify the meanings obtained from the data (Kiger & Varpio, 2020). An abductive approach was used for the thematic analysis. The analysis process was first done deductively, informed by the OIP theory, then an inductive analysis approach followed, for justification of themes, and to give room for the emergence of new themes (Earl Rinehart, 2021; Johnson et al., 2020; Rashid et al., 2019). The thematic analysis process in this study followed guidelines from Swain (2018). A cross-case analysis was also performed to highlight the similarities and differences across the cases. This analysis was done to support the generalisability of the findings (Adams et al., 2022; Vohra, 2014). The reported findings included narratives explaining how certain AI technologies were used for certain tasks. It also included a cross-case report in a tabular format, highlighting the similarities and differences across the cases.

The OIP theory was used as the theoretical framework in this study. However, this theoretical framework did fully influence the qualitative design, as this would have hindered the quality and level of induction of the qualitative research (Johnson et al., 2020). Clarke et al. (2015), Swain (2018), and Vaismoradi et al. (2013) outline certain steps for thematic analysis, which were employed in this study. The steps are depicted in Figure 4-1.

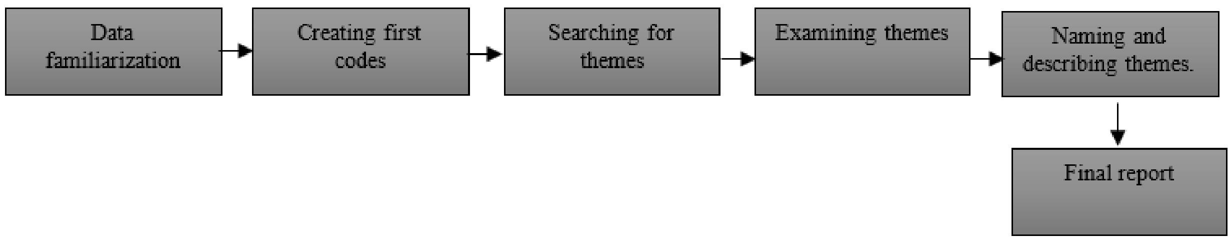


Figure 4-1: Steps involved in thematic analysis (Consolidated from Clarke et al., 2015; Swain, 2018; Vaismoradi et al., 2013)

4.8.1 Data familiarisation

Data familiarisation is the first and most crucial step in the thematic analysis process. Data familiarisation was accomplished by listening to the audio recordings and transcribing them. After the interviews were conducted, each interview recording was played back, listened to, and transcribed (Clarke et al., 2015). The transcribe option on Microsoft Word^{TM} was used for the initial transcription, with each audio recording imported into Microsoft Word to be transcribed. The raw transcription was then reviewed, along with the audio recording, and edited to ensure that the transcript accurately captured the audio recordings. This process produced accurate transcripts of all interview sessions.

After the interview transcription was performed, the Microsoft word documents were imported into NVIVO version 20^{TM} analysis software. A folder was created for the three commercial banks, and the documents containing the transcribed audio recordings were imported into their respective folders. A total of 20 files were imported into NVIVO. These 20 files contained transcripts of audio recordings from 20 respondents.

4.8.2 Codes identified in this study

Codes were identified by rereading the interview transcriptions and breaking them down into smaller units of data excepts. These excerpts were grouped under specific names. The coding process involved noting essential points related to the research question and demarcating these points (Kiger & Varpio, 2020). Table 4-4 shows four of the codes obtained from the thematic analysis process in this study.

Table 4-4: Codes obtained from the thematic analysis process in this study

Codes	Description
Analytical tools	Data analytics tools and querying tools used to extract and analyse data
Machine learning algorithms	Machine learning algorithms used by data professionals in the banks
Customer needs	Customer needs that lead to the decision by banks to implement and use AI technologies
Data needs	The types of structured or unstructured data, needed for predictive and descriptive analysis

4.8.3 Themes developed in this study

After the identification of codes, the next process was the development of themes. Because this research employed the OIP theory, four main themes were immediately developed from the codes. These themes were information processing needs, information processing capabilities, fit, and business optimisation outcome. After identifying these themes, the transcripts were read again to ensure that the identified themes were in line with the codes under them. The names given to the initial themes served as the final naming convention for the themes. Table 4-5 shows three of the themes developed during the thematic analysis process in this study.

Table 4-5: Themes developed during the thematic analysis process in this study

Themes	Codes	Description
Information processing capabilities	Machine learning algorithms	Machine learning algorithms used by data professionals in the banks
Information processing needs	Customer needs	Customer needs that motivated the banks to use AI technologies
	Data needs	The types of structured or unstructured data, needed for predictive and descriptive analysis
Business optimisation outcome	Customer satisfaction	Technologies that led to customer satisfaction.

4.8.4 Emergence of new themes

After the deductive analysis phase of the abductive thematic analysis process, and inductive analysis followed. This analysis led to the emergence of new themes which were not adequately captured by the constructs in the OIP theory. These themes were AI and BI technology awareness, and data professionals. Table 4-6 shows the themes that emerged from the inductive analysis process in this study

Table 4-6:Themes that emerged from the inductive analysis phase in this study

Themes	Description
Data professionals	The skills and functions of the data professionals working in the BI departments in the commercial banks
AI and BI technology awareness	Managers and staff awareness and knowledge of the use of AI and BI technologies in the commercial banks.

The first part of the abductive thematic analysis process was done deductively and was informed by the OIP theory. This process produced four themes. The interview transcripts were then reviewed again to ascertain that the developed themes were an accurate representation of the data extracts they contained, as well as the corresponding codes under them. For this review process, an inductive approach was taken. This review process led to the emergence of new themes. The review of the codes and themes inductively helped preserve the integrity of this qualitative research. The process of discovering new themes ended the thematic analysis process that was conducted in this research study.

4.8.5 Thematic map

The themes obtained from the deductive phase of the thematic analysis process were information processing needs, information processing capabilities, fit, and business optimisation outcome. The themes that emerged from the inductive phase were AI and BI awareness, and data professionals. Figure 4-2 shows the thematic map of the themes and their respective codes.

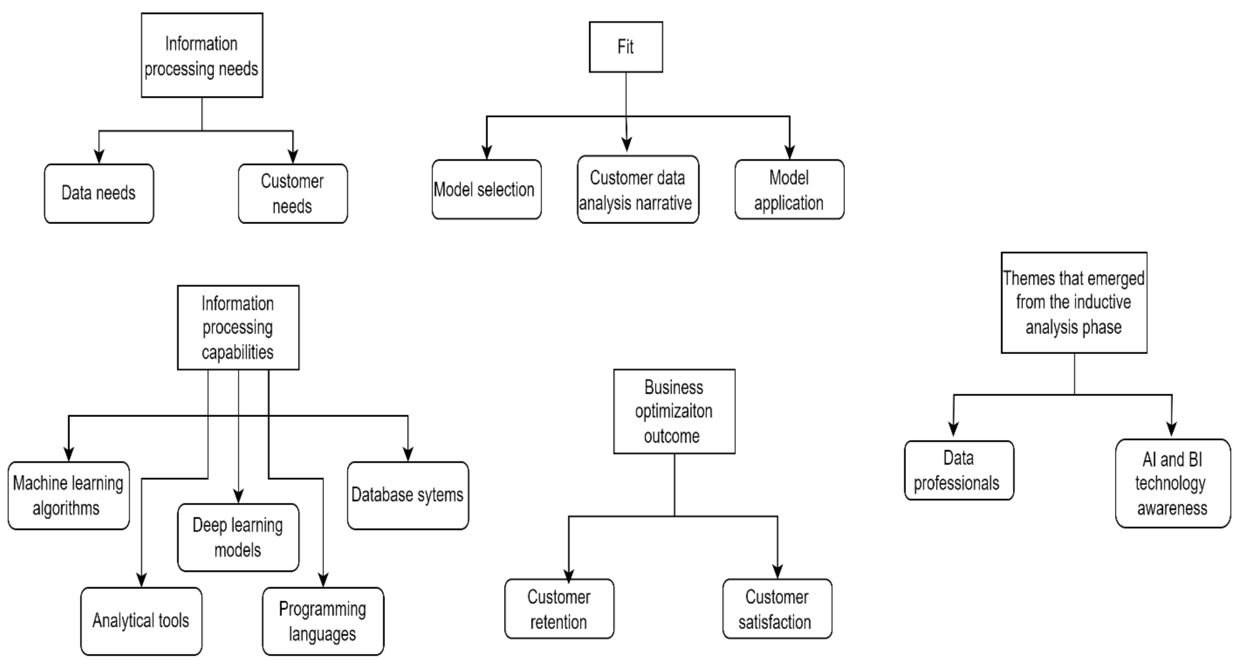


Figure 4-2: Thematic Map showing all the themes in this study

4.9 Research reliability and validity (trustworthiness)

Reliability and validity in qualitative studies are evaluated in specific terms such as dependability, credibility, confirmability, and transferability (Golafshani, 2003). Reliability and Validity are critical concepts in the evaluation of qualitative studies (Golafshani, 2003). However, they do not manifest themselves in the same way as in quantitative studies. In quantitative studies, reliability and validity can be measured by performing certain tests on the data collected, however, in qualitative studies, these tests do not apply (Golafshani, 2003).

The study ensured confirmability by:

- Providing justifications for the use of the OIP theory (Nowell et al., 2017). This is documented in the theoretical foundation chapter (Chapter 4).
- Providing justifications for using an abductive thematic analysis approach (see section 4.8)
- Providing an audit trail, in the form of a research flow table, to show the methods used for this study (see Table 4-1).

Each of these methods and choices were justified in their respective sections. The pilot test carried out using the semi structured interview questions also contributed to the dependability of the study (Kallio et al., 2016).

Credibility was established by persistent observation during the interview process, data triangulation, and member checking (Guion et al., 2011; Nowell et al., 2017). Therefore, the data extracts from the interview sessions at the various banks were compared and evaluated against each other to ensure the trustworthiness of the collected data. This was also done to prevent biases from a particular bank. Member checking was done by sending interview transcriptions to four respondents, to ensure that the transcriptions adequately captured the interviewee's answers (see Appendix N for copies of emails sent to respondents).

Transferability in this study was ensured by:

- Providing detailed information about the steps taken to develop the research instrument; guidelines by Kallio et al. (2016), Qu and Dumay (2011), and Turner (2010) were used for the questionnaire building and the typology of the questions (see Appendix B and C for more details on the questionnaire building process).
- Keeping an open mind during the interview process to avoid bias and projection of preconceived beliefs and definitions onto the interviewees.
- Refraining from evocating certain emotions such as sadness or disappointment, to improve the quality of the interview process.

- Providing a detailed explanation of the banking industry in Nigeria (see Appendix J), a brief description of the Nigerian context (See Appendix K), and information on the use of AI in Nigeria (see Section 1.1.2).
- Providing description of the cases, and a brief of the case selection process (see Sections 5.2 and 4.5.2).

Reliability and validity were also established in this research by providing justifications for case selection, performing a documentary review of online reports (See Appendix L), and using suitable methods to answer research questions (Anderson, 2017).

4.10 Ethics and confidentiality

The study obtained an ethics approval from the University of Cape Town (See Appendix I). Following that, informed consent and voluntary participation of the respondents was achieved. This was done by sending consent forms that gave details of the type of information and access required for the study. Participants were also informed of the freedom to withdraw their consent at any time if necessary. The anonymity and confidentiality of the respondents was ensured by not revealing their names in this study. The interview sessions were conducted in private rooms and permission was sought from the interviewees to record the sessions for transcription purposes (Arifin, 2018).

Data transcription and interpretation were performed independently to ensure that information about respondents were kept private (Arifin, 2018). Written or oral confirmation of participation was also obtained from the head of the BI departments at the commercial banks, before the scheduled interview date and times (See Appendix M). Before the interviews began, participants were briefed once more on the interview process, and their consent was confirmed. The interview transcripts were stored in a secure folder.

4.11 Research limitation

This study was limited by its scope, which focused only on Nigerian commercial banks that utilised AI technologies in their BI departments. It was also restricted by the cross-sectional timeframe, due to the stipulated completion time for the research study.

4.12 Chapter summary

A qualitative approach was appropriate to achieve the main objective of this research study, which was to explore how commercial banks in Nigeria used AI technologies for customer retention and satisfaction. The chapter provided the qualitative methods used to achieve the research objectives of this study.

Chapter 5 : Case Description

This chapter begins by providing information about the Nigerian banking industry. This was done to give an understanding of the banking industry within the context of this study. The chapter then proceeds to give a description of the banks selected for this study. Information about their years of existence, services delivered, and the BI departments are provided in this chapter.

5.1 The Nigerian banking industry

The Nigerian banking industry consists of commercial, microfinance, merchant and mortgage banks, all under the jurisdiction of the Central Bank of Nigeria (CBN) (Aguda, 2023; Akinwumi & Aideloje, 2023; Bernard et al., 2023; Iorkaa et al., 2021; Sharimakin, 2023).

- Commercial banks provide credit facilities, retail banking services, foreign exchange services, and deposit and withdrawal services to customers.
- Microfinance banks offer financial services to low-income individuals.
- Merchant banks provide wholesale banking services or investment services to customers.
- Mortgage banks specialise in providing mortgage loans.
- Deposit banks accept deposits from customers and create credit.

There are 19 commercial banks in the country, all the banks are headquartered in Lagos state and governed by CBN. This study focused on Commercial banks in Nigeria, because they provided a wider range of services to the general population, in contrast to the other types of banks. They had robust technologies and departments, which were necessary to provide the information needed for this study (Aguda, 2023; Bernard et al., 2023).

CBN is responsible for establishing certain operating standards and guidelines for the banks in the Nigerian banking industry (Olaniyi et al., 2023). The Nigerian banking industry is subject to regulations from CBN. CBN is the pinnacle of the Nigerian banking industry and serves as a policy enforcer and compliance inspector (Olaniyi et al., 2023). CBN acts as a regulator, overseeing the ethical handling of these data and ensuring their conformity with international data management standards (Olaniyi et al., 2023).

5.2 Description of banks selected for this study

Three banks were selected for this study. Per the assurance of anonymity given to the banks, the banks were given pseudonyms: Bank A, Bank B, and Bank C. This section provides descriptions of the BI department, and the technologies use in the three banks. The profile of the banks is shown in Table 5-1.

Table 5-1: Profile of banks selected banks

	Bank A	**Bank B**	**Bank C**
Number of employees	> 1000	> 4000	> 2000
Number of respondents interviewed	6	7	7
Years of existence	70	33	107
Services provided	Retail, SME, cooperation, treasury, trade services, and financial advisory services	Deposits, savings accounts, loans, internet banking, and advisory services	Deposits, savings accounts, loans, and internet banking services

5.2.1 Bank A

The BI department in Bank A was referred to as the Data Analytics department. The department consisted of the data engineering unit, data analysis unit, data science unit, data governance unit, and BI unit.

The bank A used ML algorithms such as the Microsoft pre-trained transformer model (GPT-4) to build a customer chat support bot. The sentiment intensity analyser was used for sentiment analysis of unstructured data scraped from social media feeds. LR and k-means algorithms were used for customer churn and customer segmentation. Recommendation engines were used for product recommendations.

The data analytics department was responsible for the development of numerous self-service dashboards. These dashboards enabled managers to interact with data themselves and draw insights from the dashboards for prompt decision-making. The bank used Microsoft Power BI for data analysis and visualisation. Dashboards were created on the Microsoft Power BI desktop application and published on the Microsoft Power BI service platform. However, due to the cost associated with the licensing of Microsoft Power BI to various employees and managers, the software engineering team developed a middleware platform. This platform mirrored the Microsoft Power BI service environment and allowed access to all staff and managers using their active directory login credentials. This prevented the need for Microsoft Power BI licensing for all staff and managers, thereby saving costs. The name of this middleware platform was not disclosed by the bank for privacy reasons.

5.2.2 Bank B

The BI department in Bank B was referred to as the Data Analytics and Data management office. This office consisted of the data engineering team, the data quality and assurance team, the visualisation team, and the data science team. Bank B leveraged on the Microsoft tenant and, hence, phased out other BI tools. Therefore, Microsoft Power BI was the main visualisation and data analytics tool.

The bank B used Naïve Bayes algorithms, and the credit scoring algorithm for predicting customer churn and determining which customers were qualified for credit facilities. The credit scoring algorithm was also used for building loan propensity models. Other models such as anomaly detection models and the k-means algorithm were used to analyse transaction patterns to prevent fraud, and group customers into various segments for personalised messaging.

5.2.3 Bank C

The Data Analytics team in Bank C consisted of data engineering, data science, data analytics, reporting analytics, and the automation team. Bank C used the KNN algorithm for customer segmentation. The Naïve Bayes was used for speculation when dealing with whether a customer would take out a loan or not, while the DT algorithm was used to pinpoint actualities rather than speculation. Other models used were the simple Bayesian model and the random forest regression model.

The bank C relied on Microsoft Power BI for data manipulations and visualisation and used Structured query language (SQL) Server Reporting Services (SSRS), and SQL Server Integration Services (SSIS) for reporting and data integration. These tools were used to create charts, graphs, dashboards, and reports that helped provide insight to business executives. These insights were then used to make customer-related decisions. These decisions helped to attract new customers and retain and satisfy existing customers.

5.3 Chapter summary

This chapter provided information about the Nigerian banking industry. The chapter also described the cases in this study and provided information about the analytics department in each of the banks, and the machine learning algorithms used by the banks.

Chapter 6 : Research Findings

This chapter presents the key findings from the data analysis process to answer this study's research questions. The chapter begins by providing information about the themes that emerged from the inductive analysis phase of the thematic analysis process in this study. These themes are awareness of AI and BI technologies in the banks and the data professionals who work in the BI department. The rest of the findings are then presented to answer the research questions, starting with the sub-questions, before the main research question. The chapter further states the outcome of the use of AI technologies in the commercial banks and highlights future technological developments. The chapter also presents the cross-case analysis findings, and a refined version of the OIP theory, titled ‘Nigerian commercial bank information processing view’.

6.1 AI and BI technology awareness in the commercial banks

Data professionals in the commercial banks noted that the banking industry in Nigeria, lagged the rest of the world when it came to the awareness of the use of AI technologies. Although the use of BI technologies remained frequent in Nigerian commercial banks, AI was still a growing field, and managers and staff had minimal knowledge of the use of AI technologies. Managers’ lack of knowledge about AI technologies, made it challenging for the data scientist to communicate the results obtained from using certain AI technologies. Hence the managers and the staff in the banks were constantly informed and educated about AI technologies.

Staff at Bank A were aware of the capabilities of BI technologies and were comfortable using the information obtained from BI technologies to make quick decisions. However, data scientists at the bank insisted that awareness of the use of AI technologies was still a continuous process within the organisation. The data scientists noted that as a bank they were still in the process of ensuring data literacy in all departments. Various data literacy programs were often organised by data scientists to train staff and boost their knowledge and understanding of the use of AI technologies for data analysis

> *“There's even a course that I am trying to design now that we want to like send to them [managers], so we can be speaking the same language because it's stressful”.* [Respondent 1A. Data scientist]

Bank B had a made significant growth in terms of making data-driven decisions. In the past, the analytics team would have to push solutions to the managers, but in recent times, the managers had grown more aware of what could be obtained with proper analysis of data. They, therefore, now approached the data analytics team to ask them to develop certain dashboards and analytical reports. Bank B used BI tools to make data-driven decisions. Employees in Bank B were more informed about BI and analytics.

BI thrived in bank C, with great progress in aspects such as descriptive analytics. Managers at Bank C understood BI tools and often asked for reports, dashboards, and insights to be generated from the data. However, sales personnel and other bank employees involved in day-to-day operations still lacked the necessary knowledge required to interpret the insights produced by the data analytics team. They rather preferred data in Microsoft Excel formats, using rows and columns.

6.2 Data professionals in the BI department of the commercial banks

The data professionals in the BI department at the banks consisted of data engineers, data scientists, data quality and governance specialists, data analysts, business analysts, and BI developers. Data engineers gathered customer data from various sources and were responsible for cleaning, transforming and storing the data in a central database. Data scientists embarked on ML projects that assisted bank managers in making informed decisions to increase customer retention and reduce churn. Data quality and governance specialists ensured that the data fed to various ML algorithms by the data scientists were clean and of good quality. Data analysts analysed and transformed data into captivating visuals that provided succinct information for managers to make informed decisions. Business analyst helped to identify and translate business needs into understandable concepts for the BI team. BI developers provided data intelligence solutions using analytics tools. These data professionals had the required skills necessary to use the AI technologies, analytical tools, database systems, and programming languages that were used to meet customer needs.

The Data professionals reported to the management in the banks, and communicated the results obtained from using AI technologies for various tasks. The management in the bank were responsible for the allocation of resources for purchasing AI technologies and the employment of the data professionals with the skills required to use these technologies.

Examples of the skills noted by the data professionals are:

- Data engineering and cloud infrastructural skills
- Data analysis and visualisation skills
- Proficiency in python programming
- Data manipulation skills
- Proficiency in using machine learning algorithms
- Problem solving skills
- Database management skills

6.3 AI technologies used in the commercial banks

The AI technologies the commercial banks used were captured under the information processing capabilities construct of the OIP theory. The following sub-sections present the AI technologies.

6.3.1 Machine learning algorithms

The banks used ML algorithms to analyse customer data for customer retention and satisfaction. Table 6-1 shows the machine learning algorithms used in each of the banks and the tasks which they were applied for.

Table 6-1: List of machine learning algorithms used in the Nigerian commercial banks

	Customer segmentation for personalised messaging	**Predicting customer churn**	**Product recommendation**	**Predicting loan collection credibility**
Bank A	K-means algorithm	Logistic regression K-means algorithm	Recommendation engines	Credit scoring algorithms
Bank B	K-means algorithm	K-means algorithm	Recommendation engines	Credit scoring algorithms Naïve Bayes algorithm
Bank C	K-means algorithm	K-nearest neighbour algorithm	Recommendation engines	Naïve Bayes algorithm Random forest regression algorithm Simple Bayesian model

Bank A used ML algorithms such as LR and k-means algorithms for customer churn and customer segmentation. Recommendation engines and credit scoring algorithms were used for product recommendations and credit scoring. Models like the sentiment intensity analyser were used for sentiment analysis of unstructured data scraped from social media feeds, and the Microsoft pre-trained transformer model (GPT-4) was used to build a customer chat support bot.

Bank B used the Naïve Bayes algorithm, and the credit scoring algorithm for predicting customer churn and determining which customers were qualified for credit facilities. The credit scoring algorithm was also used for building loan propensity models. Anomaly detection models and the k-means algorithm were used to analyse transaction patterns to prevent fraud, and group customers into various segments for personalised messaging.

Bank C used the KNN algorithm for customer segmentation. The Naïve Bayes was used for speculation when dealing with whether a customer would take out a loan or not, while the DT algorithm was used to pinpoint the actualities. The simple Bayesian model and the random forest regression model were also used for predicting loan collection credibility.

6.3.2 Deep learning models

The banks did not use DL models due to the lack of computational resources. Also, some of the models being built by the data scientists had not reached the optimal level of accuracy for use in the production environment.

> "*Currently, there are no deep learning models in production because we are just moving all our infrastructure to Microsoft Azure and that will give us the required computing power and the resources to run them*". [Respondent 2A, Data scientist]

The data scientists were aware that the need to use DL models would eventually arise due to the constant growth of customer data. They were, therefore, making plans towards that. Some of these plans included fully migrating on-premises data to the cloud for more computational power and using big data analytics tools for data storage and analysis.

AI technologies were built using programming languages, customer data was stored in databases, and the data analysis output of the machine learning algorithms were displayed using visualisation tools. Hence the banks additionally used programming languages, visualisation tools and database systems. These tools were utilised to store and process customer data. These technologies were also captured under the information processing capabilities construct of the OIP theory. The following sub-sections present the database systems, programming languages, and analytical tools.

Database systems: The commercial banks used on-premises and cloud database systems to store customer data. Banks A and B used Microsoft Azure cloud database systems and were in the process of migrating all their data on their on-premises units to the cloud database. Therefore, a hybrid system consisting of both cloud and on-premises databases was in place for both banks. Bank C relied solely on their on-premises Oracle database.

> "*Currently in the bank, we do a hybrid. Hybrid is a combination of On-PREM and Cloud"*. [Respondent 5A, Data engineer]

> "*We run Oracle SQL here*" [Respondent 16C, Data scientist]

Programming languages and analytical tools: The commercial banks used analytical tools such as Microsoft Power BI for data visualisation, and other Microsoft Power Platform applications such as Power Apps, Power Automate, SQL Azure and SQL Workbench. All these applications were available under the Microsoft tenant. The Microsoft tenant was employed by Banks A, B and C because it provided access to various Microsoft applications, all integrated and connected. Banks A, B and C also used the Python programming language for coding. The programming languages were run on the Jupyter integrated development environment. These analytical tools and programming languages we used along with the ML algorithms to analyse customer data for customer retention and satisfaction.

6.4 Needs that motivated the commercial banks to use AI technologies

The growth of data and the needs of customers motivated the use of AI technologies in Nigerian commercial banks. These needs were captured under the information processing needs construct of the OIP theory. The following sub-sections present the data and customer needs.

6.4.1 Data needs

Data needs in the banks grew as the number of customers was growing. The growth in customer data influenced the processes within the BI department and led to the use of AI technologies in the banks. The data professionals in the BI departments in the banks used various types of customer data for analysis. These datasets were grouped into structured and unstructured datasets. Examples of these datasets are shown in Table 6-2.

Table 6-2: Types of datasets analysed by the commercial banks

Data format	Data types
Structured	• Customer demographic data (age, name, occupation) • Transactional data (debit and credit details of customer accounts)
Unstructured	• Telemetry data obtained from online banking applications (page views, click-through rate, user acceptance data, and user behaviour data) • Customer comments scraped from social media platforms like Twitter and Facebook

Most of the data analysed in the BI department in the banks were structured. Structured datasets were stored in on-premises relational databases like MySQL powered by Oracle or cloud databases like Azure and were extracted using a structured query language. Unstructured datasets were less frequently analysed in the banks. Unstructured datasets were stored in nonrelational databases like Mongo DB and were exported in JavaScript Object Notation (JSON).

> "*Structured datasets are customer demographics, transaction data, debit, and credit, where customers are spending their money and the likes and financial statements*". [Respondent 10B, Data scientist]

> "*For the unstructured part of data, let's say data coming in from Twitter, Facebook. This kind of data is in textual format*". [Respondent 9B, Data scientist]

6.4.2 Customer needs

Customers in Nigeria were aware of what AI could be used for. This awareness informed their needs. The needs of Nigerian customers were:

- The need for personalised messaging:
- The need for product recommendations
- The need to ascertain loan collection credibility status
- The need for credit scoring

These needs led to the employment of AI technologies such as ML algorithms and the use of other predictive analytics tools. Data scientists in the banks noted that customer needs within the bank were viewed as business needs by the management. The managers in the banks always looked at customer needs from a business standpoint and evaluated the benefits it would bring back to the bank in terms of revenue.

> "*I think one need that drives the use of AI and machine learning that we currently use is the need to satisfy customers*". [Respondent 1A, Data scientist]

> "*Customers today, want a bank that can attend to their need, even before the need arises*". [Respondent 9B, Data scientist]

> "*I would say that what prompted many of our works around that [AI] was basically because the managers wanted to study how customers behave*". [Respondent 19C, Data analyst]

Data scientists in the banks used ML algorithms to meet customer needs. An example was the use of classification techniques and segmentation models to segment various customers, for personalised messaging. The needs of customers and the growth of data led to the use of AI technologies by the commercial banks. Database systems, programming languages and visualisation tools were also used in addition to the AI technologies. All these tools were used to meet data and customer needs.

6.5 The use of AI technologies in the commercial banks

Data scientists at the commercial banks selected certain models for the analysis of customer data. The process of model selection and the use of the models for analysing customer data were classified under the fit construct of the OIP theory.

6.5.1 Model Selection

Model selection captured the process of determining the algorithm that was appropriate for a task. The selection of a model was dependent on the nature of the task or problem identified, and the domain knowledge of the data scientists.

i. Nature of task

The nature of a task was important for model selection. Data scientists at Bank B noted that the nature of the task presented, determined the kind of model that was selected. For example, if the bank managers required customers to be re-segmented for the purpose of targeting, product selling or marketing awareness, then the data scientists would immediately know that the task required the use of a classification algorithm. Data scientists at Bank B further noted that a classification model, which enabled the separation of customers into categories of groups, based on certain characteristics, would be the most appropriate for this task.

Another example given by the data scientists at the banks, was a case where the managers noticed that there had been a decline in the number of active customers and needed to ascertain the factors that were causing this decline. When presented with this kind of task, the data scientists would immediately know to use a regression model. A regression model was appropriate for this task because it would allow a deep dive into the behaviour of customers to determine the factors that were affecting customer transactability. The data scientists further noted that the linear regression algorithm would be used for this task.

ii. Domain knowledge

A good domain knowledge of ML algorithms allowed the data scientists at the commercial banks to identify various models that could solve an identified problem. Knowing the various distinctions of ML models, such as the models for supervised and unsupervised learning, was key to identifying the right algorithms, as well as keenly paying attention to the type of data related to the problem. In addition to this, however, certain tests had to be applied to ascertain the model that could solve the identified problem most accurately. Examples of such tests were:

- Receiver operating characteristic curve (ROC) for determining the performance of classification models.
- Grid search cross-validation (Grid search CV) to determine the optimal combination of hyperparameters for a given model.
- Evaluating model precision scores such as recall and accuracy.

"So, it depends on the domain knowledge, and it depends on the nature of the task you are trying to achieve. For projects where you make binary decisions, you can use classification algorithms" [Respondent 3A, Data scientist]

"I will have to use the models that fit my objective, run these models and then do a comparison using the ROC to see which one is the best". [Respondent 16C, Data scientist]

6.5.2 Customer data analysis narrative

The customer data analysis narrative section provides the general steps that the data scientist in the commercial banks applied to analyse customer data. This process also involved inputs from data analysts, data engineers, business analysts, and the data quality and governance specialist.

i. Understanding the business problem

The first and most important step was understanding the business problem or need. The business was the top management in the banks who brought forward a particular need. This need could be predicting customer churn or segmenting customers for personalised messaging. Once this need was identified, it was brought to the data scientists. The data scientists, managers, and the business analyst would then sit together to understand the need and develop a goal.

ii. Data gathering

The developed goal informed the next step, which was the data gathering process. At this stage, the data scientist identified the various data sources that contained the data relevant to solving the problem. The data engineer was responsible for ensuring easy access to the data source and provided the data scientist with the data required.

iii. Data cleaning

After data gathering, came data cleaning. The removal of null values and ensuring the correct data types and correct data structure was part of this process. The data quality and governance specialist ensured that the data provided to the data scientist was of good quality, to minimise the data cleaning process.

iv. Exploratory data analysis

During the exploratory data analysis stage, the data scientist looked at the behaviour of the data, to understand what possible insights the data could give. The data scientist also looked for abnormalities, and outliers in the data.

v. Feature engineering

Feature engineering involved selecting the most appropriate features to feed into the model, dropping unnecessary features, and determining if there was a need to select additional features.

vi. Model building

At this stage, the data scientist trained and tested the model. The datasets were split into test and train datasets, usually 80% for the training dataset and 20% for the test dataset. After training and testing, the data scientist would then fit the algorithm on the model (in the case where it was a regression model) and evaluate it in terms of recall, F1 score, precision, and accuracy, depending on the nature of the task. For example, some tasks required the data scientist to prefer recall over precision. If the model performance was not accurate enough, the data scientist would then go back to the exploratory data analysis and feature engineering processes. Methods such as feature dimensionality reduction, and hyperparameter tuning could then be applied to ensure optimal model performance.

vii. Visualisation of results

Once the model performance was satisfactory, the results were sent to a database, with the location given to the data analyst, who was responsible for visualising the results using Microsoft Power BI.

viii. Model performance tracking

After visualising the results, the continuous use of the model and the results obtained were then tracked by the data scientist to ensure that it was meeting the required goal.

6.5.3 Model applications

This section describes how certain models were used for certain tasks in the commercial banks. It provides descriptions of how ML algorithms were used for predicting customer churn, customer segmentation, product recommendation, and predicting loan collection credibility.

i. Predicting customer churn

Predicting customer churn was a frequent need of the commercial banks. It was important for the banks to know which customers were likely to leave, to enable preventive measures. These measures included targeted advertising, and personalised messaging. When the need identified was the prediction of customer churn, a classification model was the most appropriate model. In the case where a classification model such as the LR or the k-means algorithm was used, pertinent data would first need to be gathered. These data included: ‘number of years the customer had spent in the bank’, ‘last transaction data', 'number of transactions performed by the customer over a certain period', 'customer turnover', gender, 'entrenchment level', 'number of bank products used by the customer’ and ‘transaction history’. By integrating these datasets into the model, an output of ‘1’ or ‘0’ would be produced. An output of ‘1’ would signify that the customer would likely churn, and an output of ‘0’ would signify that the customer would likely stay.

> “*For the last classification we did, it helped us classify customers that were going to churn. The people we are interested in are the ones who return ‘1’, which means that they are going to churn. So, we chase after them with aggressive marketing*”. [Respondent 9B, Data scientist]

Data scientists at Bank C also gave a brief narrative of the use of classification models for predicting customer churn. They stated that when using a model for customer churn prediction, the first step would be to determine the factors that were contributing to a customer leaving the bank. The data scientists would collect data: ‘customer account balance', 'customer occupation', 'customer locality', 'customer demography' and ‘customer transaction rate’. To get these data, they would write structured query language scripts that would fetch the data from the database. After this, they would then get more information from the customer data, such as which customers were making high sales, which customers were making low sales, and their age range. After this process, they would then ascertain the features which would be important for the model, by a process known as feature engineering. This process also enabled the removal of outliers and anomalies. After the data scientists had determined the datasets that fitted well with the classification model they had selected, they could then classify customers into churners and non-churners brackets. This was done by feeding the model with test and train data, for the model to determine a pattern for feature churn predictions.

ii. <u>Customer segmentation</u>

Classification algorithms were also used for the segmentation of customers into different segments, to serve each segment of customers in a personalised manner. Customers were segmented into groups: 'high income', 'low income', 'high savers', and 'low savers.' Grouping customers into these various segments proved useful to the banks, as it provided information on the customers who brought in a high amount of money to the banks and the customers who brought in the least amount of money. The banks, therefore, knew which customers to prioritise.

Bank B used the LR algorithm to gain valuable insight from their customer data. Data scientists at the bank reported an instance when a classification algorithm was used to re-classify an existing customer into a different bracket. This customer had initially opened a tier three savings account. This account allowed a daily transaction inflow and outflow of 1 million Naira. However, over time the customer began to earn more money, but remained in the tier three savings account bracket. With the use of a classification algorithm, the data scientists noticed that the customers’ earning had improved to that of the High-net-worth individual bracket. The customer was then moved up to the High-net-worth individual bracket, which included certain benefits, like access to airport lounges during flight trips.

Data scientists at Bank A used classification algorithms to segment customers for personalised messaging. Certain brackets were used to distinguish customers with different earnings. A big catcher was noted as a high-income earner, and a young hustler was noted as a middle-income earner. The segmentation of customers into these brackets enabled the bank to send pristine messages to each bracket.

> *"What this segmentation helps us to do is understand the customer. When we understand these customers, we understand their lifestyle. This helps us to now recommend personalised products to those customers".* [Respondent 1A, Data scientist]

iii. Product recommendations

Data scientists at Bank C used recommendation engines to track the spending patterns of customers. The results obtained were then used to inform product recommendations. For example, if a recommendation engine identified that a customer would always spend a certain amount of money every week at a particular restaurant and discovered that the customer did not have that amount for the new week. The model would recommend a short-term loan to the customer, provided the model had also identified that the customer had a stable source of income.

iv. Predicting loan collection credibility

Bank B used the k-means algorithm to classify customers based on credit scores, to determine loan collection credibility. A loan propensity model was also used to inspect the earning consistency of customers, to ascertain that they had a stable means of income and could pay back the loan given. The models would require data like: 'amount earned', 'frequency of earning', 'customer age', 'customer demography data', and 'credit score'.

> "*Part of the check is that if I am going to offer you a loan, I need to see evidence that you earn money consistently, and if you have a good credit score, those are the things that qualify a customer for any type of loan*". [Respondent 9B, Data scientist]

The data scientists at the commercial banks used classification algorithms and recommendation engines to gain useful insights into customer behaviour and make decisions. These decisions led to customer retention and customer satisfaction. As seen from the narratives, the product recommendation engines played a key role in the recommendation of products, while the classification algorithms were used to predict customer behaviour, send personalised messages, determine customer credit score and predict loan collection credibility.

6.6 Business optimisation outcome

Customer retention and satisfaction was the outcome of the fit between information processing needs and information processing capabilities in this study. When the data scientist in the commercial banks used ML algorithms to meet customer needs, the outcome was customer satisfaction and retention. The data scientists in the banks gave the following examples of the use of ML models for customer satisfaction and retention.

i. Loan propensity model

The loan propensity model was used to study customers' patterns, earnings, and habits. This provided insights into customer priorities. Hence, the banks used this model to suggest loan options for their customers even before the need arose. This led to customer satisfaction and retention in Banks A and B.

> "*If I give you a loan as a customer, you will be satisfied. If I do credit scoring and I tell you at the end of the month, you are qualified to take ten million naira, you will also be satisfied as a customer*". [Respondent 10B, Data scientist]

ii. Sentiment analysis

Natural language processing was used to analyse customer sentiments from online media, to know what customers said about certain products. This helped the banks to know which products to discontinue and which products to focus on. This led to customer satisfaction and retention in Banks A and B.

iii. Product recommendations

Recommendation engines were used to provide suggestions to customers who used online banking platforms, via a process known as the next best offer and the next best action. For example, if a customer was to purchase a particular product through the online banking platform, a complementary product would be suggested. Also, if a customer had already requested a service on the online banking platform, and had not received a response, the relationship manager of that customer would automatically be notified to check the delay. This led to customer satisfaction and retention in banks B and C.

> *"We also have what we call a recommendation engine. That was also a model for customer retention and customer satisfaction"*. [Respondent 12B, Data scientist]

iv. Customer segmentation

Classification models were used to segment customers into various brackets to send personalised messages, ensuring that each piece of information or product recommended was relevant to the customer bracket it was intended for. Segmentation of customers into various brackets also proved useful for predicting churners and non-churners and improving overall customer relationships in Banks A, B, and C.

> "*Another part is segmentation, what this segmentation helps us to do is to understand the customer better. It also keeps the relationship going and helps us to retain them*". [Respondent 2A, Data scientist]

6.7 Future technological developments in the commercial banks

Certain technological developments were also noted by the data scientists in Banks A and C. In Bank A, the lead data scientist noted that plans were in place to build a chatbot for their mobile banking platform. This chatbot would allow customers to dispute a failed transaction immediately, by interacting with the chatbot, and would prevent the need for customers to call the customer care service or visit the bank. In addition to this, there was also a plan to develop AI capabilities for suggesting the next best products for customers while they used the mobile banking platforms, and an application, that would be able to track customers spending patterns. In Bank C, data scientists noted the development of a loan propensity model, and all banks hinted at the use of DL models in the future.

> *"There is a customer self-service tool, kind of a chatbot, that is going to be deployed to the mobile banking platform of the bank. This will help customers dispute transactions at the point of making those transactions".* [Respondent 2A, Data scientist]

6.8 Cross-case analysis findings

The cross-case analysis in this study involved comparing the reports of the single cases, to determine the similarities and differences in the tools used and activities performed across the cases. A cross-case analysis is important for promoting the generalisability of results in qualitative studies (Adams et al., 2022). A cross-case report highlighting the main similarities and slight differences between each case in this study is displayed in Table 6-3.

Table 6-3: Cross-case analysis findings

	Bank A	**Bank B**	**Bank C**
Analytical tools	• Microsoft Power BI • Microsoft Excel • Microsoft power platform applications	• Microsoft Power BI • Microsoft Excel • Microsoft power platform applications	• Microsoft Power BI • Microsoft Excel • Microsoft power platform applications
Data integration and extraction tools	• Structured query language • Microsoft SQL Azure and MySQL workbench	• Structured query language • Microsoft SQL Azure and MySQL workbench	• Structured query language • SQL Server Integration Services and SQL Server Reporting
Database storage Systems	• On-premises and azure cloud storage systems (Hybrid)	On-premises and azure cloud storage systems (Hybrid)	• On-premises Oracle SQL server and database
Machine leaning algorithms used	• Microsoft pre-trained transformer model (GPT-4) • Sentiment intensity analyser • Logistic regression • K-means algorithm • Recommendation engines	• Naïve Bayes algorithm • Credit scoring algorithms • Anomaly detection algorithms • K-means algorithm • Recommendation engines	• K-nearest neighbour algorithm • Simple Bayesian model • Naïve Bayes algorithm • Random forest regression algorithm • Recommendation engines
Deep leaning models used	None	None	None
Tasks which the machine learning algorithms are used for	• Sentiment analysis • Customer churn prediction • Customer segmentation • Product recommendation • Building chatbots	• Customer churn prediction • Predicting loan collection credibility • Credit scoring • Customer segmentation	• Customer segmentation • Predicting loan collection credibility • Customer churn prediction • Product recommendation
Outcome of using machine learning algorithms	• Sentiment analysis of customer comments for better product development • Customer segmentation for personalised messaging • Recommending products and loan options to customers	• Sentiment analysis of customer comments for better product development • Recommending products and loan options to customers • Customer segmentation for personalised messaging	• Recommending products and loan options to customers • Customer segmentation for personalised messaging

From Table 6-3, slight differences can be seen between the banks, notably, the use of hybrid storage systems in Banks A and B and on-premises storage systems in Bank C. Also, the use of SQL server integration and reporting services for data integration and extraction in Bank C, and MySQL workbench and Microsoft SQL Azure in Banks A and B. Other differences can be seen in the types of ML algorithms used by the various banks and the outcomes gotten from the algorithms used. There was no reason given for these differences, except that the banks had different preferences when it came to the technologies used. Despite these differences, all the banks used ML algorithms for customer retention and satisfaction and obtained similar benefits.

6.9 The Nigerian commercial bank information processing view

The Nigerian commercial bank information processing view was developed by the researcher in this study as a refined version of the OIP theory. This refined version was created following the outcome of using a theory in qualitative research, where the research output can refine an existing theory as noted by Taylor (2018).

The following sub-sections provide information about the themes captured by the OIP theory and themes not captured by the OIP theory in this research study. The need for the Nigerian commercial bank information processing view, and what it captured in this research study is also provided in this section.

6.9.1 Themes captured by the OIP theory

The OIP theory was used in this research to capture the needs of customers and the growth of customer data as information processing needs. The theory captured ML algorithms, and DL models as information processing capabilities, along with the database systems, analytical tools and programming languages. The theory captured the processes of model selection, the customer data analysis narrative, and model application as ways to match information processing capabilities to information processing needs. Lastly, the theory captured the business optimisation outcome of customer retention and satisfaction as performance.

6.9.2 Themes not captured by the OIP theory

Themes such as AI and BI technology awareness, and the skills of the data professionals who worked in the BI departments, were not captured by the OIP theory. These themes emerged from the inductive phase of the abductive analysis process.

6.9.3 The need for the Nigerian commercial bank information processing view

The Nigerian commercial bank information processing view was developed to additionally capture AI and BI technology awareness and skills of the data professionals who worked in the BI departments. This refined version also provided information on the specific tools, and technologies used in Nigerian commercial banks, as well as the customer needs, and processes involved in the analysis of customer data. Figure 6-1 shows The Nigerian commercial bank information processing view

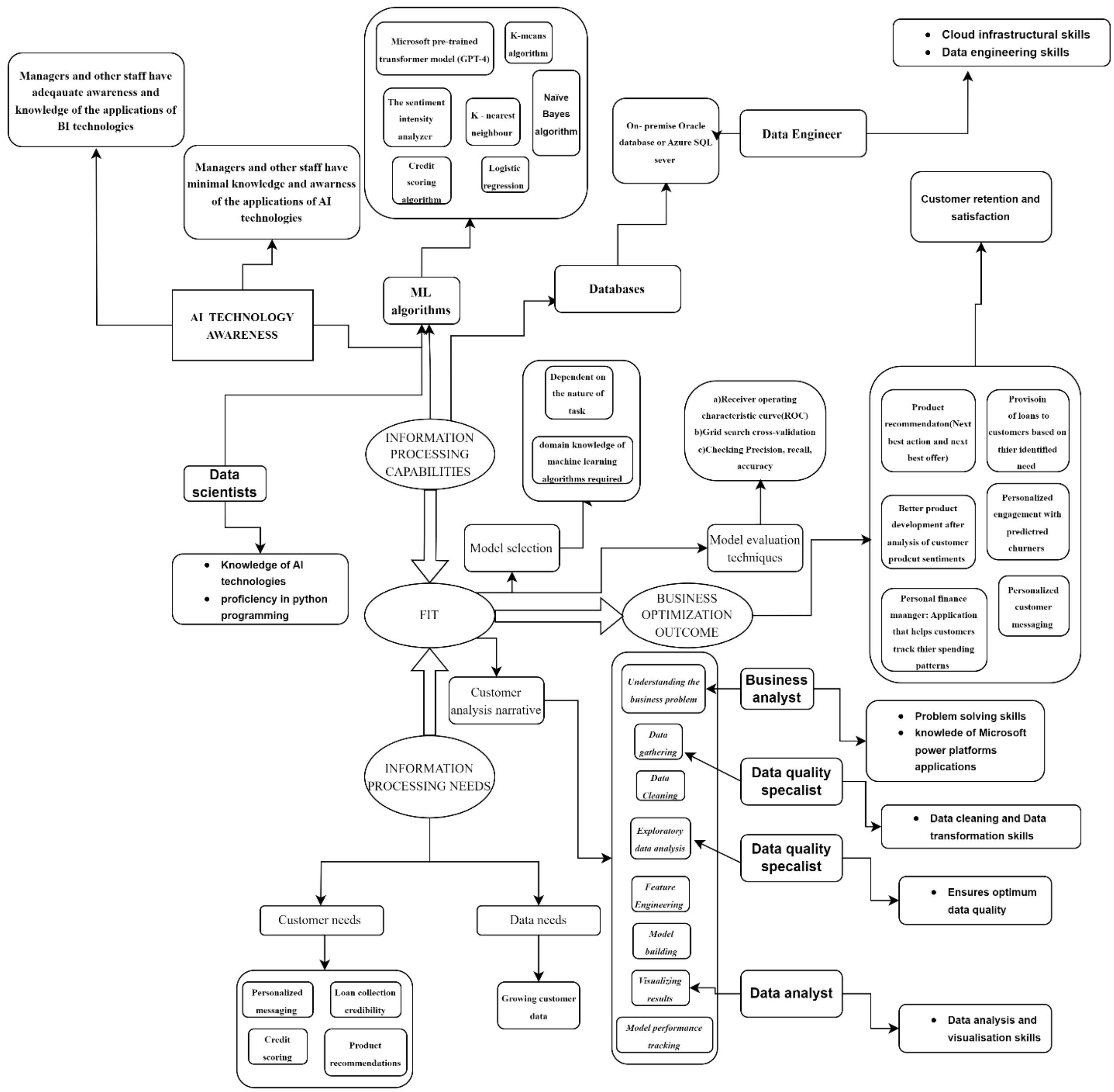


Figure 6-1: The Nigerian Commercial Bank Information Processing view

In Figure 6-1, the awareness of AI and BI technologies falls under the information processing capabilities, so too does the skills of data professionals in the BI department. The awareness of AI and BI technologies by managers and other staff in the bank was important to enable the data scientists communicate the results obtained from using AI technologies. The data professionals were responsible for making use of the AI technologies to analyse customer data. DL models are not shown in Figure 6-1, because the commercial banks did not use any.

6.10 Summary of findings and chapter

The findings in this study showed that needs such as the growth of data, and the needs of customers motivated the use of AI technologies in Nigerian commercial banks. These needs were seen as information processing needs and classified as data and customer needs. The findings showed that data professionals in the commercial banks used various ML algorithms along with other analytical tools, and database systems to process store and analyse customer data for retention and satisfaction. However, they did not use any DL models. The findings also showed that managers and other staff had adequate knowledge of the use of BI technologies and minimal knowledge and awareness of the use of AI technologies. Lastly, the findings showed that ML algorithms were used for tasks such as customer segmentation, predicting customer churn, product recommendation, and predicting loan collection credibility.

This chapter reported the findings of this study and answered the research questions. The chapter presented the business optimisation outcomes obtained from using AI technologies in the commercial banks, the future considerations of the banks, and the cross-case analysis findings. The chapter also presented the Nigerian commercial bank information processing view.

Chapter 7 : Discussion of Findings

This chapter discusses the research findings. The needs that motivated Nigerian commercial banks to use AI technologies and the AI technologies used are compared to the literature. The process of analysing customer data and the awareness of AI and BI technologies in Nigerian commercial banks are also discussed, along with their relation to the literature.

7.1 Customer needs in Nigerian commercial banks

The customer needs noted in Nigeria are not dissimilar to those seen in various banks around the world (Durwin, 2023; Haddadi et al., 2022; Sadiq et al., 2022; Seid & Woldeyohannis, 2022). Meeting customer needs is a major priority in the banking industry. Banks in Africa and around the world also provide personalised banking services to customers by using AI technologies (Durwin, 2023; Haddadi et al., 2022; Sadiq et al., 2022). Therefore, the needs reported by the data scientists in the commercial banks were not only peculiar to the Nigerian banking Industry. Customers in Nigeria had an awareness of what AI technologies could be used for. Due to this awareness, customers expected banks to be able to predict their needs before they arose. Hence commercial banks majorly applied AI technologies to provide personalised messages, product recommendations and loans to customers. This was done to keep customers satisfied and to prevent them from switching to competitor banks.

7.2 Data needs in Nigerian commercial banks

The banks used cloud and on-premises databases to store customer data. Cloud databases have proven to be an excellent solution for handling large amounts of data. The flexibility, scalability, and cost-effective nature of these databases represent the main reason for their popularity (Karunamurthy et al., 2023). Hence the use of the Azure cloud database in Nigerian commercial banks. However, due to security issues in cloud systems, lack of control of the underlying infrastructure, the risk of data loss, and compliance with data regulatory policies, some banks in Nigeria, have not fully migrated their data to cloud databases (Mkhatshwa and Mawela, 2023). As in the case of Bank C, the use of the Oracle on-premises database enabled the commercial bank to maintain control of the underlying infrastructure and security of data.

7.3 The AI technologies used in the commercial banks

The commercial banks in this study used similar ML algorithms as other banks highlighted in the literature for the prediction of customer churn (see Table 6-1). Banks in Ethiopia also use the KNN and LR for customer churn prediction (Seid & Woldeyohannis, 2022), while banks in India use chatbots to provide 24-hour real-time customer support (Durwin, 2023). Hence, these developments were not peculiar to the Nigerian banking industry. What was peculiar, however, was the reason for using such models. Since the managers in the banks had not fully grasped a proper understanding of AI technologies, data scientists within the banks were limited to using the simplest models, which were easily explainable. Hence, they seldom used other ML models such as the SVM and DL models seen in the literature (Haddadi et al., 2022; Seid & Woldeyohannis, 2022).

The banks in Nigeria did not use DL models such as ANN for data mining, or customer churn, because of the lack of computational resources. Also, because some of the models being built by the data scientists had not reached the optimal level of accuracy for use in the production environment. Hence, unlike other banks that used DL models for certain tasks (Durwin, 2023; Kanan et al., 2023; Seid & Woldeyohannis, 2022), the commercial banks in Nigeria solely relied on ML models for predictive analysis.

The model selection process, and the steps taken for the analysis of customer data by the data scientist in the commercial banks, are not different from the general processes and steps used when analysing customer data (see Section 2.4). Steps such as data gathering, data cleaning, feature engineering, model selection, and evaluation remained the same. The commercial banks in Nigeria, also used AI technologies for similar tasks shown in the literature, such as understanding customer behaviour, segmenting customers for personalised messaging, and predicting customer churn (Bharadiya, 2023b; Seid & Woldeyohannis, 2022).

7.4 AI and BI technology awareness in Nigerian commercial banks

The managers and staff in the banks had a good knowledge of BI tools and were adept at navigating BI visualisation tools, like the Microsoft Power BI dashboard. These findings agree with previous literature which highlights Nigerian commercial banks as frequent users of BI tools (Nithya & Kiruthika, 2021). However, a proper understanding of AI technologies was still at a minimal level for bank managers. This was because managers in the Nigerian commercial banks, did not have much knowledge about AI technologies and their usefulness. The emergence of this issue in the Nigerian commercial banks is not unusual. There remains a lack of knowledge on the part of managers in multiple industries across Africa, regarding the use of AI technologies (Ade-Ibijola & Okonkwo, 2023).

Managers in commercial banks provide the necessary funding to purchase AI technologies; their understanding of what AI technologies offer is therefore important to facilitate the necessary funding (Neumann et al., 2022). Managers who do not have technical knowledge about AI systems cannot provide the required support and funding for the purchase and use of AI systems (Chen & Chen, 2021). This trend was evident in the Nigerian banking industry, as managers' resistance to the use of complex machine learning models, limited data scientists to using simpler easily explainable machine learning models. This hindered the use of complex machine learning models, with higher precision and accuracy, such as the SVM. Data scientists at the commercial banks, therefore set up digital literacy programs to help educate managers and staff on the benefits and applications of AI technologies.

7.5 Business optimisation outcome

Retaining and satisfying customers was the main outcome obtained from using AI technologies in the Nigerian commercial banks. Product recommendations, personalised messaging, and customer classification helped to keep customers satisfied and led to customer retention. The benefits of using these models in the Nigerian banks are identical to the benefits obtained from using ML algorithms and other AI technologies in banks around the world (Desai et al., 2021; Hassanien et al., 2023; Kanan et al., 2023; Nwanakwaugwu et al., 2023).

7.6 Chapter summary

The chapter discussed the needs that motivated Nigerian commercial banks to use AI technologies, and the AI technologies used, in comparison to the literature. The process of analysing customer data and the awareness of AI and BI technologies in Nigerian commercial banks were also discussed, along with their relation to the literature in this study.

Chapter 8 : Conclusion

This study provided the information processing needs and information processing capabilities in commercial banks in Nigeria. This knowledge was obtained by interviewing 20 data professionals across three commercial banks in Nigeria. Thematic analysis was used to analyse the data collected.

The information processing needs in the banks motivated the use of information processing capabilities. This study provided narratives of how information processing capabilities were used to match information processing needs in the banks. Information processing needs in this study were customer and data needs. Information processing capabilities were AI technologies, database systems, programming languages and visualisation tools. This study further provided a refined version of the organisational informational processing theory peculiar to the study's context.

8.1 Summary of answers to research questions

8.1.1 What AI technologies do Nigerian commercial banks use for business optimisation?

Findings showed that commercial banks in Nigeria used ML algorithms for customer retention and satisfaction as a form of business optimisation. The banks did not however use any DL models because of the lack of computational power, and because the models being developed were not accurate enough for deployment onto the production environment. The Python programming language was used to build ML algorithms, databases were used to store customer data and analytical tools were used to visualise the data analysis output. These technologies were information processing capabilities. AI technologies such as the sentiment intensity analyser, LR, k-means algorithm, Naïve Bayes algorithm, KNN, and recommendation engines, were used for various tasks. For example, sentiment analysis, customer segmentation, customer churn prediction, predicting loan collection credibility and product recommendations. The AI technologies used in the commercial banks were captured using you the information processing construct of the OIP theory

8.1.2 What motivates Nigerian commercial banks to use AI technologies?

Findings showed that the growth of structured and unstructured customer data, and the needs of customers motivated the use of AI technologies in Nigerian commercial banks. Large amounts of data require proper storage and efficient analysis. Hence commercial banks employed Database systems to adequately store customer data, and AI technologies to efficiently analyse the data. The information obtained from the analysis of customer data was used to make informed decisions about customer behaviour. Examples of customer needs were personalised messaging, product recommendations, ascertaining loan collection credibility status, and credit scoring. Customer and data needs were captured using the information processing needs construct of the OIP theory

8.1.3 How do commercial banks in Nigeria use AI technologies for business optimisation?

Findings showed that data professionals in the banks used various procedures to determine the appropriate model for certain tasks. The model selected was often dependent on the nature of the problem, and the domain knowledge of the data scientist. After model selection, data professionals in the banks followed certain steps to analyse customer data and evaluate the model performance based on the problem identified.

The data scientists at the commercial banks used classification algorithms and recommendation engines to gain useful insights into customer behaviour and make decisions. These decisions led to customer retention and customer satisfaction. Product recommendation engines also played a key role in the recommendation of products, while the classification algorithms were used to predict customer behaviour, send personalised messages, determine customer credit scores and predict loan collection credibility. The Fit construct of the OIP theory captured how AI technologies were applied for business optimisation in the commercial banks.

8.2 Research contributions and implications

Contribution to literature: This study was conducted to explore how commercial banks in Nigeria used AI technologies for customer satisfaction and retention. By doing so, it has contributed to the literature, specifically to the field of AI within the Nigerian banking industry. This study also provided theoretical contributions by presenting the Nigerian commercial bank information processing view as a refined version of the organisational informational processing theory pertinent to commercial banks in Nigeria.

The findings in this study, provided information on the specific information processing needs (customer and data needs) and specific information processing capabilities, used in Nigerian commercial banks. This study also provided insight into how information processing capabilities were used to meet the needs of customers. To the knowledge of the researcher, a qualitative approach providing such information about the use of AI techniques in Nigerian commercial banks has not been previously reported in literature.

Practical Contributions: This study employed semi-structured questionnaires for interviewing data professionals in the BI department in the commercial banks. Therefore, it provided practical contributions, like detailing the major customer and data needs in the Nigerian commercial banks, the popularly used ML models, analytical tools, and their applicability to various tasks. This knowledge is important for other banks in the Nigerian banking sector that may eventually use AI technologies due to the constant growth of customer data.

The study showed that the managers in the commercial banks had a good knowledge of BI technologies, but little knowledge of AI technologies. Therefore, managers in the Nigerian banking industry should be educated on the benefits, and capabilities of AI technologies, and data professionals should continue to organise data literacy programs for the managers

The study showed that the constant growth of data necessitated the need for flexible and scalable databases that could provide the necessary computing power needed to support AI technologies. However not all banks in Nigerian currently use cloud databases. Hence Nigerian commercial banks need to thoroughly vet the security controls of cloud service providers and inspect how data privacy and security are maintained. Cloud providers should also provide detailed mitigation strategies of how security threats are mitigated to commercial banks, in a bid to build trust with banks in Nigerian commercial banks.

This study also showed that DL models were not yet used by the commercial banks selected for this study. Although the study hinted that the banks planned to use such models in the future. The lack of computational power, and lack of perfection of the models in terms of accuracy, hindered the use of DL models in the commercial banks.

Theoretical contribution: This study employed the OIP theory as a theoretical framework. It refined the framework by capturing the skills of data professionals in the BI department and the AI and BI technology awareness in the Nigerian commercial banks. The refined version of this framework was titled ‘Nigerian commercial bank information processing view’.

8.3 Limitations of the study and future research suggestions

The main limitation of this study is the lack of a wider generalisation of these findings to other types of banks in the Nigerian banking industry. This study only explored the use of AI technologies in Commercial banks in Nigeria. Therefore, although there is a high level of certainty of the findings due to the multiple case study design; these findings may not be generalised to all types of banks in the Nigerian banking industry. This study was also purely qualitative; hence the lack of quantitative data also limits the robustness and generalisability of the findings.

Another limitation of this study is the time frame. Due to the cross-sectional time frame for this research, some AI technologies under development by the commercial banks could not be fully documented. Further studies can adopt a different approach and a longitudinal time frame to adequately capture AI technologies under development, how they are used, and the results obtained. It will also be intriguing for future studies to explore when the need for the use of DL models arises in Nigerian commercial banks. What prompts the need, what DL models are used, and what additional resources are employed to handle such models.

This study was limited to data professionals in the BI departments of the commercial banks because they constantly used AI technologies. Therefore, this study did not capture the manager's perspective on the use of AI within the banks. Future studies can adopt this approach because it can help to understand managers' perceptions of the use of such technologies and improve management support for the use of these technologies.

8.4 Final summary

This study explored the use of AI technologies in Nigerian commercial banks for business optimisation (customer satisfaction and retention). This study focused on three commercial banks and highlighted data professionals as social actors who used these AI technologies. This study agreed that AI technologies can be used as information processing capabilities to address information processing needs in Nigerian commercial banks. It remains to be seen whether all banks within the Nigerian banking industry would eventually use AI technologies, and whether banks that currently use ML models will eventually use DL models. However, commercial banks in Nigeria must continue to use data analytics technologies and embrace AI technologies to handle the constant growth of customer data, and the varying needs of customers, to remain competitive. It will be intriguing for future studies to explore when the need for the use of DL models arises in Nigerian commercial banks. What prompts the need, what DL models are used, and what additional resources are employed to handle such models.

REFERENCES

Abdulsalam, S. O., Arowolo, M. O., Saheed, Y. K., & Afolayan, J. O. (2022). Customer churn prediction in telecommunication industry using classification and regression trees and artificial neural network algorithms. *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, *10*(2), 431-440. https://doi.org/10.52549/ijeeiv10i2.2985

Achara, M., & Eke, H. O. Business Intelligence Systems and Service Delivery Performance of Telecommunication Companies in Port Harcourt. www.arcnjournals.org

Adams, C. R., Barrio Minton, C. A., Hightower, J., & Blount, A. J. (2022). A Systematic Approach to Multiple Case Study Design in Professional Counseling and Counselor Education. *Journal of Counselor Preparation and Supervision*, *15*(2). https://digitalcommons.sacredheart.edu/jcps/vol15/iss2/24

Ade-Ibijola, A., Okonkwo, C. (2023). Artificial Intelligence in Africa: Emerging Challenges. In: Eke, D.O., Wakunuma, K., Akintoye, S. (eds) Responsible AI in Africa. Social and Cultural Studies of Robots and AI. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-031-08215-3_5.

Adom, D., Yeboah, A., & Ankrah, A. K. (2016). Constructivism philosophical paradigm: Implication for research, teaching, and learning. *Global journal of arts humanities and social sciences*, *4*(10), 1-9. https://d1wqtxts1xzle7.cloudfront.net

Agidi, R. C. (2019). Artificial intelligence in Nigeria financial sector. *International Journal of Electronics and Information Engineering*, *11*(1), 40-47. https://doi.org/10.6636/IJEIE.20190911(1).01

Aguda, O. O. (2023). An analysis of the legal and institutional framework for the control of banking operations in Nigeria. *Ajayi Crowther University Law Journal*, *4*(1). https://aculj.acu.edu.ng/index.php/lj/article/viewFile/44/42

Ahmad, H., Hanandeh, R., Alazzawi, F., Al-Daradkah, A., ElDmrat, A., Ghaith, Y., & Darawsheh, S. (2023). The effects of big data, artificial intelligence, and business intelligence on e-learning and business performance: Evidence from Jordanian telecommunication firms. *International Journal of Data and Network Science*, *7*(1), 35-40. https://doi.org/10.5267/j.ijdns.2022.12.009

Ahmed, S. F., Alam, M. S. B., Hassan, M., Rozbu, M. R., Ishtiak, T., Rafa, N., Mofijur, M., Shawkat Ali, A., & Gandomi, A. H. (2023). Deep learning modelling techniques: current progress, applications, advantages, and challenges. *Artificial Intelligence Review*, *56*(11), 13521-13617. https://doi.org/10.1007/s10462-023-10466-8

Ahrens, T., & Dent, J. F. (1998). Accounting and organizations: realizing the richness of field research. *Journal of 10*. https://web.s.ebscohost.com/

Ajayi, F. A., & Olalekan, A. (2023). Artificial Intelligence & Internal Audit Quality of Commercial Banks in Nigeria. *International Journal of Management and Economics Invention*, *9*(04). https://doi.org/10.47191/ijmei/v9i4.05

Akinwumi, O. I., & Aideloje, S. (2023). The Buhari Administration and The Mortgage Sector: An Impact Analysis. *Wukari International Studies Journal*, *7*(1), 13-13. https://wissjournals.com.ng/index.php/wiss/article/download/124/111

Al-Ababneh, M. M. (2020). Linking ontology, epistemology and research methodology. *Science & Philosophy*, *8*(1), 75-91. https://ssrn.com/abstract=3708935

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. *PACIS*, *4*, 231-245. https://aisel.aisnet.org/pacis2018/37

Alsheibani, S. A., Cheung, D., & Messom, D. (2019). Factors inhibiting the adoption of artificial intelligence at organizational level: A preliminary investigation. Retrieved from https://researchmgt.monash.edu

Alsheibani, S., Messom, C., & Cheung, Y. (2020). Re-thinking the competitive landscape of artificial intelligence. https://scholarspace.manoa.hawaii.edu

Alupo, C. D., Omeiza, D., & Vernon, D. (2022). Realizing the potential of ai in africa: It all turns on trust. In *Towards Trustworthy Artificial Intelligent Systems* (pp. 179-192). Springer. http://www.vernon.eu/publications/2021_Delmus_Alupo_et_al.pdf

Ameen, N., Sharma, G. D., Tarba, S., Rao, A., & Chopra, R. (2022). Toward advancing theory on creativity in marketing and artificial intelligence. *Psychology & marketing*, *39*(9), 1802-1825. https://doi.org/ 10.1002/mar.21699

Anderson, V. (2017). Criteria for evaluating qualitative research. *Human Resource Development Quarterly*, 1-9. https://pure.port.ac.uk/

Arifin, S. R. M. (2018). Ethical considerations in qualitative study. *International journal of care scholars*, *1*(2), 30-33. https://doi.org/10.31436/ijcs.v1i2.82

Ayoubi, E., & Aljawarneh, S. (2018). Challenges and opportunities of adopting business intelligence in SMEs: Collaborative model. Proceedings of the First International Conference on Data Science, E-learning and Information Systems, 1-5. https://doi.org/10.1145/3279996.3280038

Badillo, S., Banfai, B., Birzele, F., Davydov, I. I., Hutchinson, L., Kam-Thong, T., Siebourg-Polster, J., Steiert, B., & Zhang, J. D. (2020). An introduction to machine learning. *Clinical pharmacology & therapeutics*, *107*(4), 871-885. https://doi.org/10.1002/cpt.1796

Baştanlar, Y., & Özuysal, M. (2014). Introduction to machine learning. *miRNomics: MicroRNA biology and computational analysis*, 105-128. https://doi.org/10.1007/978-1-62703-748-8_7

Bayraktar, E., Tatoglu, E., Aydiner, A. S., & Delen, D. (2023). Business analytics adoption and technological intensity: An efficiency analysis. *Information Systems Frontiers*, 1-18. https://doi.org/10.1007/s10796-023-10424-3

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: Current state and future opportunities. *MIS Quarterly Executive*, *19*(4). https://dio.org/10.2139/ssm.3741983

Bernard Azolibe, C., Okonkwo, J. J., & Obi-Nwosu, V. O. (2023). Technology-based banking and bank deposit: The Nigerian commercial banks' experience. *African Journal of Science, Technology, Innovation and Development*, *15*(1), 31-44.https://doi.org/10.1080/20421338.2021.2015164

Bharadiya, J. P. (2023a). A Comparative Study of Business Intelligence and Artificial Intelligence with Big Data Analytics. *American Journal of Artificial Intelligence*, *7*(1), 24. https://doi.org/ 10.11648/j.ajai.20230701.14

Bharadiya, J. P. (2023b). Machine Learning and AI in Business Intelligence: Trends and Opportunities. *International Journal of Computer (IJC)*, *48*(1), 123-134. https://www.researchgate.net/publication/371902170

Boina, R., Achanta, A., & Mandvikar, S. (2023). Integrating data engineering with intelligent process automation for business efficiency. *International Journal of Science and Research (IJSR)*, *12*(11), 1736-1740. https://doi.org/10.21275/SR231123225415

Borokini, F., Wakunuma, K., & Akintoye, S. (2023). The Use of Gendered Chatbots in Nigeria: Critical Perspectives. In *Responsible AI in Africa: Challenges and Opportunities (pp. 119-139)*. Springer International Publishing Cham. https://library.oapen.org/bitstream/handle/20.500.12657/60787/1/978-3-031-08215

Bouchrika, I. (2024). What is Information Processing Theory? Stages, Models & Limitations in 2024. *Education*. Retrieved Friday, December 27, 2024 from https://research.com/education/what-is-information-processing-thoery

Britannica. (2023). *Climate of Nigeria*. Retrieved Thursday, June 8, 2023, from https://www.britannica.com/place/Nigeria/Settlement-patterns.

Busayo, T., Igbekoyi, O., Oluwagbade, O., Adewara, Y., Dagunduro, M., & Boluwaji, Y. (2023). Artificial Intelligence and Service Quality of Telecommunication Firms in Nigeria. *Journal of Economics, Finance and Accounting Studies*, *5*(3), 203-214. https://doi.org/10.32996/jefas.2023.5.3.16

Busse, C., Meinlschmidt, J., & Foerstl, K. (2017). Managing information processing needs in global supply chains: A prerequisite to sustainable supply chain management. *Journal of Supply Chain Management*, *53*(1), 87-113. https://doi.org/10.1111/jscm.12129

C.B.N (2024). Macroeconomic Outlook: *Price Discovery for Economic Stabilisation*. Retrieved Thursday, December 25, 2024, from www.cbn.gov.ng

Çelebi, H. İ. (2021). Artificial intelligence applications in management information systems: a comprehensive systematic review with business analytics perspective. *Artificial Intelligence Theory and Applications*, *1*(1), 25-56. https://dergipark.org.tr/en/pub/aita/issue/70741/1137794

Chen, H., Li, L., & Chen, Y. (2021). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of Management Analytics*, 8(1), 36-68. https://doi.org/10.1080/23270012.2020.1852895

Clarke, V., Braun, V., & Hayfield, N. (2015). Thematic analysis. *Qualitative psychology: A practical guide to research methods*, *3*, 222-248.

Damenu, T. K., & Beaumont, C. (2017). Analysing information security in a bank using soft systems methodology. *Information & Computer Security*, *25*(3), 240-258. https://doi.org/10.1108/ics-07-2016-0053

Dennehy, D., Griva, A., Pouloudi, N., Dwivedi, Y. K., Mäntymäki, M., & Pappas, I. O. (2023). Artificial intelligence (AI) and information systems: perspectives to responsible AI. *Information Systems Frontiers*, *25*(1), 1-7. https://doi.org/10.1007/s10796-022-10365-3

Desai, Z., Anklesaria, K., & Balasubramaniam, H. (2021). Business Intelligence Visualization Using Deep Learning Based Sentiment Analysis on Amazon Review Data. 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), 1-7, IEEE. https://doi.org/10.1109/icccnt51525.2021.9579786

Durwin, A.S. (2023). Artificial intelligence (AI) in the Indian banking sector. *Artificial intelligence (AI)*, *52*(8). Http://www.journal-iiie-india.com/1_aug_23/3_online.pdf

Earl Rinehart, K. (2021). Abductive analysis in qualitative inquiry. *Qualitative Inquiry*, *27*(2), 303-311. www. https://doi.org/10.1177/1077800420935912

Ekpa, M., Onuora, J., & David, S. (2023). Artificial Brain Power and Corporate Performance of Listed Deposit Money Banks in Nigeria. *International Journal of Economics and Financial Management (IJEFM)*, *8*(2), 97-111. https://doi.org/10.56201/ijssmr.v8.no1.2022.pg32.40

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*, *24*(5), 1709-1734. https://www.academia.edu

Fadlullah, Z. M., Tang, F., Mao, B., Kato, N., Akashi, O., Inoue, T., & Mizutani, K. (2017). State-of-the-art deep learning: Evolving machine intelligence toward tomorrow's intelligent network traffic control systems. *IEEE Communications Surveys & Tutorials*, *19*(4), 2432-2455. https://doi.org/10.1109/COMST.2017.2707140

Feldman, D., & Himmelstein, J. (2013). *Developing Business Intelligence Apps for SharePoint: Combine the Power of SharePoint, LightSwitch, Power View, and SQL Server 2012*. " O'Reilly Media, Inc.".

Gadzala, A. (2018). Coming to Life: Artificial Intelligence in Africa. Atlantic Council–Africa Centre. *ISSUU. Retrieved from* https://issuu. com/atlanticcouncil/docs/coming_to_life-artificial_intelligence.

Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, *4*(3), 28-36. https://doi.org/10.1287/inte.4.3.28

Gammelgaard, B. (2017). The qualitative case studies. *The International Journal of Logistics Management*, *28*(4), 910-913. https://doi.org/10.1108/ijlm-09-2017-0231

Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *The qualitative report*, *8*(4), 597-607. http://www.nova.edu/ssss/QR/QR8-4/golafshani.pdf

Guion, L. A., Diehl, D. C., & McDonald, D. (2011). Triangulation: establishing the validity of qualitative studies: FCS6014/FY394, Rev. 8/2011. *Edis*, *2011*(8), 3-3. https://journals.flvc.org/edis/article/download/126893/126533

Gwagwa, A., Kraemer-Mbula, E., Rizk, N., Rutenberg, I., & De Beer, J. (2020). Artificial Intelligence (AI) deployments in Africa: benefits, challenges and policy dimensions. *The African Journal of Information and Communication*, *26*, 1-28. http://dx.doi.org/10.23962/10539/30361

Haddadi, S. J., Mohammadi, M. O., Bahrami, M., Khoeini, E., Beygi, M., & Khoshkar, M. H. (2022). Customer churn prediction in the Iranian banking sector. 2022 International Conference on Applied Artificial Intelligence (ICAPAI), 1-6. https://doi.org/10.1109/icapai55158.2022.9801574

Hamza, R. Y. (2019). *Impact of business intelligence on organizational value creation: A case study of Nestle Nigeria PLC* Dublin Business School]. https://esource.dbs.ie/handle/10788/3662

Hamzehi, M., & Hosseini, S. (2022). Business intelligence using machine learning algorithms. *Multimedia Tools and Applications*, *81*(23), 33233-33251. https://doi.org/10.1007/s11042-022-13132-3

Hanaysha, J. R., & Mehmood, K. K. (2022). An exploration of the effect of customer relationship management on organizational performance in the banking sector. *International Journal of Customer Relationship Marketing and Management (IJCRMM)*, *13*(1), 1-16. http://doi.org/10.4018/ijcrmm.2022010101

Hassanien, S. A., Roushdy, M., Galal, A., & Haggag, R. M. Y. (2023). Prediction of customer churn in the banking sector. *Journal of southwest Jiaotong university*, *58*(4). Https://doi.org/10.35741/issn.0258-2724.58.4.55

Iorkaa, A. A., Barma, M., & Muazu11, H. (2021). The Assessment Of Financial Institutions' awareness and Application Of Machine Learning Techniques For Credit Risk Prediction-The Case Of Nigeria. *Annals. Computer Science Series*, *19*(1). https://anale-informatica.tibiscus.ro/download/lucrari/Vol19/19-1-02-Asongo.pdf

Jaldi, A. (2023). Artificial Intelligence Revolution in Africa: Economic Opportunities and Legal Challenges. *Morocco: Policy Centre for the New South*. https://www.policycenter.ma/sites/default/files/2023-07/PP_13-23%20%28Jaldi%20%29.pdf

Johnson, J. L., Adkins, D., & Chauvin, S. (2020). Qualitative research in pharmacy education: A review of the quality indicators of rigor in qualitative research. *American Journal of Pharmaceutical Education*, *84*(1), 138-146. http://www.ajpe.org

KPMG. (2019, June 1). *Assessing the Maturity of Data & Analytics Capabilities in Nigeria*. Https://Assets.Kpmg.com. Retrieved September 1, 2023, from https://assets.kpmg.com

Kallio, H., Pietilä, A. M., Johnson, M., & Kangasniemi, M. (2016). Systematic methodological review: developing a framework for a qualitative semi-structured interview guide. *Journal of advanced nursing*, *72*(12), 2954-2965. https://doi.org/10.1111/jan.13031

Kamal, S. (2019). Research paradigm and the philosophical foundations of a qualitative study. *PEOPLE: International Journal of Social Sciences*, *4*(3), 1386-1394. https://doi.org/10.20319/pijss.2019.43.13861394

Kanan, T., Mughaid, A., Al-Shalabi, R., Al-Ayyoub, M., Elbes, M., & Sadaqa, O. (2023). Business intelligence using deep learning techniques for social media contents. *Cluster Computing*, *26*(2), 1285-1296. https://doi.org/10.1007/s10586-022-03626-y9

Karunamurthy, A., Yuvaraj, M., Shahithya, J., & Thenmozhi, V. (2023). Cloud Database: Empowering Scalable and Flexible Data Management. Quing: International Journal of Innovative Research in Science and Engineering.

Kasych, A., Yakovenko, Y., & Tarasenko, I. (2019). Optimization of business processes with the use of industrial digitalization. 2019 IEEE International Conference on Modern Electrical and Energy Systems (MEES), 522-525. IEEE http://doi.org/10.1109/mees.2019.8896531

Kaur, M., & Mohta, A. (2019). A review of deep learning with recurrent neural network. 2019 International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 460-465. https://doi.org/10.1109/icssit46314.2019.8987837

Kiger, M. E., & Varpio, L. (2020). Thematic analysis of qualitative data: AMEE Guide No. 131. *Medical teacher*, *42*(8), 846-854. https://doi.org/10.1080/0142159x.2020.1755030

Krauter, N., & Mayer, E. (2019). Does structure matter? The influence of organizational structure on information overload. In. https://www.diva-portal.org/

Krishnamoorthi, S., & Mathew, S. K. (2018). Business analytics and business value: A comparative case study. *Information & Management*, *55*(5), 643-666. https://doi.org/10.1016/j.im.2018.01.005

Kumar, P., Mokha, A. K., & Pattnaik, S. C. (2022). Electronic customer relationship management (E-CRM), customer experience and customer satisfaction: evidence from the banking industry. *Benchmarking: An International Journal*, *29*(2), 551-572. https://doi.org/10.1108/bij-10-2020-0528.

Lateef, M., & Keikhosrokiani, P. (2022). Predicting Critical success factors of business intelligence implementation for improving SMEs' performances: a case study of Lagos State, Nigeria. *Journal of the Knowledge Economy*, 1-26. https://doi.org/10.1007/s13132-022-00961-8

Livingston, J., Selvi, T., & Jenifer, C. S. (2019). A neural network-based approach for sentimental analysis on amazon product reviews. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, *8*, 469-473.

Magau, M. D., & Maritz, J. (2020). One finance: dealing with Nigeria's highly skilled talent constraints. *Emerald Emerging Markets Case Studies*, *10*(3), 1-20. https://doi.org/10.1108/eemcs-01-2020-0017

Mandal, P. C. (2018). Saturation in qualitative research: Considerations and limitations. *International Journal of Academic Research and Development*, *3*(2), 624-628.

McCormack, K. & Trkman, P (2014). The influence of information-processing needs on the continuous use of business analytics. *Information Research, 19*(3) http://Informationr.net/ir/19-3/paper636

McNamara, C. (2009) General Guidelines for Conducting Interviews. https://managementhelp.org/evaluatn/intrview.htm

Mkhatshwa, B., & Mawela, T. (2023). Cloud Computing Adoption in the South African Public Sector. *Indonesian Journal of Electrical Engineering and Informatics* (IJEEI), 11(2). https://doi.org/10.52549/ijeei.v11i2.4464

Mohajan, H. K. (2018). Qualitative research methodology in social sciences and related subjects. *Journal of economic development, environment and people*, *7*(1), 23-48. https://mpra.ub.uni-muenchen.de/85654/

Monye, O. (2023). Cashless policy initiative in Nigeria: outline of crucial socio-economic and regulatory considerations. *Journal of Money Laundering Control*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/JMLC-05-2023-0098

Moon, K., & Blackman, D. (2014). A guide to understanding social science research for natural scientists. *Conservation biology*, *28*(5), 1167-1177. https://doi.org/10.1111/cobi.12326

Morgan, H. (2022). Conducting a qualitative document analysis. *The Qualitative Report*, *27*(1), 64-77. https://hanimorgan.com/wp-content/uploads/2022/01/Hani-Morgan-Conducting-a-Qualitative-Document-Analysis-1.pdf

Neumann, O., Guirguis, K., & Steiner, R. (2022). Exploring artificial intelligence adoption in public organizations: a comparative case study. *Public Management Review*, 1-27. https://doi.org/10.1080/14719037.2022.2048685

Nithya, N., & Kiruthika, R. (2021). Impact of Business Intelligence Adoption on performance of banks: a conceptual framework. *Journal of Ambient Intelligence and Humanized Computing*, *12*, 3139-3150. https://doi.org/10.1007/s12652-020-02473-2

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International journal of qualitative methods*, *16*(1), 1609406917733847. https://doi.org/10.1177/1609406917733847

Nwanakwaugwu, A. C., Matthew, U. O., Kazaure, A. A., & Haruna, K. (2023). Data Mining Business Intelligence Applications in Retail Services Using Artificial Neural Networks. In *Handbook of Research on Cybersecurity Risk in Contemporary Business Systems* (pp. 186-210). IGI Global. https://doi.org/10.4018/978-1-6684-7207-1.ch010

Odunlami, S. A., & Oludipe, E. O. (2021). Work Stress and Employee Performance: A Study Of Selected Deposit Money Banks In Lagos And Ogun States, Nigeria. *Ilorin Journal of Business and Social Sciences*, *23*(1), 15. https://www.researchgate.net/

Ogunleye, B. O. (2021). *Statistical learning approaches to sentiment analysis in the Nigerian banking context*. Sheffield Hallam University (United Kingdom).

https://www.proquest.com/dissertations-theses/statistical-learning-approaches-sentiment/docview/2734703680/se-2

Ohiani, A. S. (2020). Technology innovation in the Nigerian banking system: prospects and challenges. *Rajagiri Management Journal*, *15*(1), 2-15. https://doi.org/10.1108/ramj-05-2020-0018

Okoliko, E., Ayetigbo, A., Ifegwu, I., & Chidiebere, N. (2023). Artificial Intelligence Impact in Revolutionizing the Nigerian Banking Industry: An Assessment of Selected Deposit Money Banks in Abuja. *Achievers Journal of Scientific Research*, *5*(2), 120-131. www.achieversjournalofscience.org

Okwor, U. D. (2022). Artificial intelligence: As a tool for combating insecurity in Nigeria. In. https://www.researchgate.net/publication/362112308

Olaniyi, O., Olaoye, O. O., & Okunleye, O. J. (2023). Effects of Information Governance (IG) on profitability in the Nigerian banking sector. *Asian Journal of Economics, Business and Accounting*, *23*(18), 22-35. https://ssrn.com/abstract=4526249

Oloruntoba-Oju, T., & van Pinxteren, B. (2023). Issues in introducing indigenous languages in higher education in Africa: The example of Nigeria. *Language Problems and Language Planning*, *47*(1), 1-23. https://www.jbe-platform.com/deliver/fulltext/lplp.22005.olo.pdf

Orji, U. E., Ezema, M. E., Ujah, J., Bande, P. S., & Agbo, J. C. (2022). Using Twitter Sentiment Analysis for Sustainable Improvement of Business Intelligence in Nigerian Small and Medium-Scale Enterprises. 2022 IEEE Nigeria 4th International Conference on Disruptive Technologies for Sustainable Development (NIGERCON), 1-5. https://doi.org/10.1109/nigercon54645.2022.9803087

Owoyemi, A., Nnaemeka, E., Benson, T. O., Ikpe, R., Nwachukwu, B., & Isedowo, T. (2023). Machine Learning Recommendation System for Health Insurance Decision Making In Nigeria. https://doi.org/10.48550/arXiv.2305.10708

Oyadeyi, O. (2024). Banking innovation, financial inclusion and economic growth in Nigeria. Journal of the Knowledge *Economy*, 15(2), 7014-7043. https://doi.org/10.1007/s13132-023-01396-5

Oyewole, S., & Salami, A. (2024). Data Protection laws of the world Nigeria. https://www.dlapiperdataprotection.com/

Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and policy in mental health and mental health services research*, *42*, 533-544. https://doi.org/ 10.1007/s10488-013-0528-y

Petit, P. (2016). Business optimization for platinum mining projects and operations. *Journal of the Southern African Institute of Mining and Metallurgy*, *116*(2), 123-130. http://dx.doi.org/10.17159/2411-9717/2016/v116n2a3

Premkumar, G., Ramamurthy, K., & Saunders, C. S. (2005). Information processing view of organizations: an exploratory examination of fit in the context of interorganizational relationships. *Journal of Management Information Systems*, *22*(1), 257-294. https://doi.org/10.1080/07421222.2003.11045841

Qu, S. Q., & Dumay, J. (2011). The qualitative research interviews. *Qualitative research in accounting & management*, *8*(3), 238-264. https://doi.org/10.1108/11766091111162070

Radhakrishnan, J., & Chattopadhyay, M. (2020). Determinants and Barriers of Artificial Intelligence Adoption–A Literature Review. Re-imagining Diffusion and Adoption of Information Technology and Systems: A Continuing Conversation: IFIP WG 8.6 International Conference on Transfer and Diffusion of IT, TDIT 2020, Tiruchirappalli, India, December 18–19, 2020, Proceedings, Part I, 89-99. Springer International Publishing. https://doi.org/10.1007/978-3-030-64849-7_9

Rahi, S., Khan, M. M., & Alghizzawi, M. (2021). Extension of technology continuance theory (TCT) with task technology fit (TTF) in the context of Internet banking user continuance intention. *International Journal of Quality & Reliability Management*, *38*(4), 986-1004. https://doi.org /10.1108/ijqrm-03-2020-0074

Rangineni, S. (2023). An Analysis of Data Quality Requirements for Machine Learning Development Pipelines Frameworks. *International Journal of Computer Trends and Technology*, *71*(9), 16-27. https://www.researchgate.net/publication/343944592

Rashid, Y., Rashid, A., Warraich, M. A., Sabir, S. S., & Waseem, A. (2019). Case study method: A step-by-step guide for business researchers. *International journal of qualitative methods*, *18*, 1609406919862424. https://doi.org/10.1177/1609406919862424

Sadiku, M. N., Fagbohungbe, O., & Musa, S. M. (2020). Artificial Intelligence in Business. *International Journal of Engineering Research and Advanced Technology*, *6*(07), 62-70. https://doi.org/ 10.31695/ijerat.2020.3625

Sadiq, M. J., Jobanputra, D., Kaushik, T. G. S., & Rao, J. S. V. (2022). Bank Customer Churn Prediction Using Machine Learning. *International Journal of Scientific Research in Computer Science, Engineering, and Information Technology (IJSECSEIT)*, *8(2)*, 334-341. https://doi.org/10.32628/ijsrcseit

Saunders, B., Sim, J., Kingstone, T., Baker, S., Waterfield, J., Bartlam, B., Burroughs, H., & Jinks, C. (2018). Saturation in qualitative research: exploring its conceptualization and operationalization. *Quality & quantity*, *52*(4), 1893-1907. https://doi. 10.1007/s11125-017-0574-8

Schmitt, M. (2023). Deep learning in business analytics: a clash of expectations and reality. *International Journal of Information Management Data Insights*, *3*(1), 100146. https://doi.org/10.1016/j.jjimei.2022.100146

Seid, M. H., & Woldeyohannis, M. M. (2022). Customer Churn Prediction Using Machine Learning: Commercial Bank of Ethiopia. 2022 International Conference on Information and Communication Technology for Development for Africa (ICT4DA), 1-6. https://doi.org/ 10.1109/ICT4DA56482.2022.9971224

Seuring, S., Stella, T., & Stella, M. (2021). Developing and Publishing Strong Empirical Research in Sustainability Management—Addressing the Intersection of Theory, Method, and

Empirical Field. *Frontiers in Sustainability*, *1*, 617870. https://doi.org/10.3389/frsus.2020.617870

Shakir, M. (2002). The selection of case studies: strategies and their applications to IS implementation case studies. Research Letters in the Information and Mathematical Sciences, 3, 69-77. http://hdl.handle.net/10179/4373

Sharda, R., Delen, D., & Turban, E. (2021). *Analytics, data science, & artificial intelligence: Systems for decision support*. Pearson.

Sharimakin, A. (2023). Microfinance bank in Nigeria: operating environment, sustainability, and welfare impact. *SN Business & Economics*, *3*(10), 183. https://doi.org/10.1007/s43546-023-00552-y

Sharma, R., & Srinath, P. (2018). Business intelligence using machine learning and data mining techniques-an analysis. 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 1473-1478). IEEE. https://doi.org/10.1109/iceca.2018.8474847

Sharma, R., Zhang, C., Wingreen, S. C., Kshetri, N., & Zahid, A. (2020). Design of blockchain-based precision healthcare using soft systems methodology. *Industrial Management & Data Systems*, *120*(3), 608-632. https://doi.org/10.1108/imds-07-2019-0401

Shollo, A., & Galliers, R. D. (2016). Towards an understanding of the role of business intelligence systems in organizational knowing. *Information Systems Journal*, *26*(4), 339-367. https://doi.org/10.1111/isj.12071

Shrestha, Y. R., Krishna, V., & von Krogh, G. (2021). Augmenting organizational decision-making with deep learning algorithms: Principles, promises, and challenges. *Journal of Business Research*, *123*, 588-603. https://doi.org/10.1016/j.jbusres.2020.09.068

Siau, K., & Wang, W. (2018). Ethical and moral issues with AI-a case study on healthcare robots. Emergent research forum (ERF). Accessed October 20. https://www.researchgate.net

Simeone, O. (2018). A brief introduction to machine learning for engineers. *Foundations and Trends® in Signal Processing*, *12*(3-4), 200-431. http://dx.doi.org/10.1561/2000000102

Skhvediani, A., Arteeva, V., & Sviridenko, M. (2019). Comparative Analysis of the Framework of Skills of a Data Analyst Job in Russia and the USA. 34th International Business Information Management Association Conference, IBIMA, 8895-8902. https://www.researchgate.net/publication/340917407

Swain, J. (2018). A hybrid approach to thematic analysis in qualitative research: Using a practical example. *Sage research methods*. https://doi.org/ 10.4135/9781526435477.

Tamang, M. D., Shukla, V. K., Anwar, S., & Punhani, R. (2021). Improving business intelligence through machine learning algorithms. 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), 63-68 IEEE. https://doi.org/10.1109/iciem51511.2021.9445344

Tavera Romero, C. A., Ortiz, J. H., Khalaf, O. I., & Ríos Prado, A. (2021). Business intelligence: business evolution after industry 4.0. *Sustainability*, *13*(18), 10026. https://doi.org/10.3390/su131810026

Taylor, L. C. (2018). Reassessing and refining theory in qualitative accounting research: An illustrative account of theorizing. *Qualitative Research in Accounting & Management*, *15*(4), 510-534. https://doi.org/10.1108/qram-09-2017-0090

Tekir, S., & Bastanlar, Y. (2020). Deep learning: Exemplar studies in natural language processing and computer vision. *Data Mining-Methods, Applications and Systems*. https://doi.org/10.5772/intechopen.91813

Tight, M. (2023). Saturation: An Overworked and Misunderstood Concept? *Qualitative Inquiry*. https://doi.org/10.1177/107780042311839

Tripathi, A., Bagga, T., & Aggarwal, R. K. (2020). Strategic impact of business intelligence: A review of literature. Prabandhan: Indian Journal of Management, 13(3), 35-48. https://doi.rog/10.17010/pijom/2020/v13i3/151175

Turner III, D. W. (2010). Qualitative interview design: A practical guide for novice investigators. *The Qualitative Report*, *15*(3), 754. http://www.nova.edu/ssss/QR/QR15-3/qid.pdf

Udoh, W. A., Nsude, I., & Oyeleke, A. S. (2022). Awareness of Artificial Intelligence for News Production among Journalists in Ebonyi state Nigeria. *International Journal of Network and Communication Research*, *7*(1), 33-45. https://www.researchgate.net/publication/372676402

Ukpong, E. G. (2022). Integration of Artificial Intelligence Applications for Financial Process Innovation by Commercial Banks in Nigeria. *AKSU Journal of Administration and Corporate Governance (AKSUJACOG)*, *2*(1), 125-137. https://aksujacog.org.ng/articles/22/04/integration-of-artificial-intelligence-applications-for-financial-process-innovation-by-commercial-banks-in-nigeria/aksujacog_02_01_09.pdf

Vaismoradi, M., Turunen, H., & Bondas, T. (2013). Content analysis and thematic analysis: Implications for conducting a qualitative descriptive study. *Nursing & health sciences*, *15*(3), 398-405.https://doi.org/10.1111/nhs.12048

Vakkuri, V., Kemell, K.-K., Kultanen, J., & Abrahamsson, P. (2020). The current state of industrial practice in artificial intelligence ethics. *Ieee Software*, *37*(4), 50-57. https://doi.org/10.1109/MS.2020.2985621

Van Norren, D. E. (2023). The ethics of artificial intelligence, UNESCO, and the African Ubuntu perspective. *Journal of Information, Communication and Ethics in Society*, *21*(1), 112-128. https://www.emerald.com/insight/1477-996X.htm

Vohra, V. (2014). Using the multiple case study design to decipher contextual leadership behaviours in Indian organizations. *Electronic Journal of Business Research Methods*, *12*(1), pp54-65-pp54-65. https://academic-publishing.org/

Yin, R. K. (2009). *Case study research: Design and methods* (Vol. 5). sage.

Young, T., Hazarika, D., Poria, S., & Cambria, E. (2018). Recent trends in deep learning based natural language processing. *IEEE Computational intelligence magazine*, *13*(3), 55-75. https://doi.org/10.1109/mci.2018.2840738

Zargar, S. A. (2021). Introduction to Convolutional Neural Networks. *Department of Mechanical and Aerospace Engineering, North Carolina State University*. https://doi.org/10.13140/rg.2.2.11572.17282

Zhao, Z.-Q., Zheng, P., Xu, S.-t., & Wu, X. (2019). Object detection with deep learning: A review. *IEEE transactions on neural networks and learning systems*, *30*(11), 3212-3232. https://doi.org/ 10.1109/tnnls.2018.2876865

Zohuri, B., & Moghaddam, M. (2020). From business intelligence to artificial intelligence. *Journal of Material Sciences & Manufacturing Research. SRC/JMSMR/102*, *3*. https://www.onlinescientificresearch.com

APPENDIX

I. Appendix A: Project Plan

Table 0-1: Project plan

Deliverables	Dates
Research Proposal Presentation	13th March 2023
Dissertation Proposal Submission	9th June 2023
Literature Review Submission	27th April 2023
Research Design Submission	25th August 2023
Ethics Approval	September 2023
Pre-test Research Instrument	October 2023
Data Collection	November 2024 –January 2024
Data Analysis & Reporting	January 2024 – March 2024
Prepare draft dissertation	April 2024 – July 2024
Final Empirical Report Submission	August 2024

II. Appendix B: Building the Research Instrument

Semi-structured interviews are popular in qualitative research, due to their flexible and conversational nature. However, they require a great deal of planning and attention to detail when crafting questions, to elicit the required responses from participants (Kallio et al., 2016; Qu & Dumay, 2011; Turner, 2010).

Qu and Dumay (2011) discussed three interview viewpoints: romanticism, neopositivism, and localism. Neopositivists view the interview process only as a tool that is applied to elicit truth in the most objective way possible. The Romanticist view the interview process as an interpersonal encounter, where rapport and connection between the interviewer and interviewee is established. Finally, for the localist, the interview process is a conversational encounter in which the interview itself can be seen as a knowledge production and reporting process. In an interview setting, the localist interviewer seeks to understand what is happening in the interviewee’s world and remains open to new developments that may arise during the interview process. The localist viewpoint is often applied in the semi structure interview processes, and thus was taken into consideration for this study. Hence, the semi-structured interview process in this study was not only seen as a tool for collecting information, but as a knowledge building process and an exploration into the phenomenon under study from the perspective of the interviewee.

III. Appendix C: Preparing for the interview & Typology of Questions

The building of questions, the interviewer's style, the setting and the environment in which the interview is conducted are all important and contribute to the uniqueness and quality of the interview process (Qu & Dumay, 2011; Turner, 2010). For example, the interpersonal skills of the interviewer largely influence the outcome of an interview process. Since interviews are generally challenging to get, an interviewer should ensure that when the opportunity presents itself, he or she makes the interviewee feel calm and comfortable (Ahrens & Dent, 1998). Before the interview, a comfortable setting was selected, as guided by the interviewee to ensure that the conversation was without outside encumbrances. The purpose of the interview was explained by sending interviewees a brief of the research study and the semi-structured questionnaire beforehand, so that they could familiarise themselves with the purpose and aim of the study. The confidentiality issues were addressed by providing the interviewees with the ethics approval obtained from the University of Cape town and letting the interviewees know that their names and the names of bank would remain anonymous during the study reporting phase (Arifin, 2018). Information about the format and duration of the interview was also sent to interviewees. The interviewees were also informed that they would be contacted at a later stage for member checking, to confirm the transcribed data.

A brief introductory rapport with the interviewee was established, to evoke calmness. Attention was paid to the responses of the interviewees, to avoid cutting short the responses of the interviewees. An open mind was kept during the interview process, to avoid bias and projection of preconceived beliefs and definitions on the interviewees. The flow of information of the interviewee was also followed during the interview process, to ensure that the interviewee shared information freely. One question was asked per time, and in the case that an interviewee’s answer strayed from the question asked, he or she was steered back in a calm way (McNamara, 2009). The interviewees were also be made aware that they could ask any questions or seek further clarification about the interview process.

Qu and Dumay (2011) also suggest certain types of questions that can be asked during an interview process to ensure a rich conversation. The questions are shown in Table 0-2.

Table 0-2: Question types for semi-structured interviews (Qu & Dumay, 2011)

Introductory questions	Introductory questions start an interview process and aim to build an initial rapport before moving to the main interview questions.
Reply questions	Reply questions are often called follow-up questions and are asked to prompt the interviewee to elaborate more on a previously asked question. The interviewer can also elicit follow-up responses by gestures such as nodding, and acts such as repeating certain points to prompt the interviewee to expound more on certain answers.
Probing Questions	Probing questions arise as the interview process develops. For example, questions like 'Would you like to give an example of this?' or 'Can you talk more about that?'
Specific Questions	Specific questions cut straight to the point. For example, 'How do you apply this technique?'
Direct Questions	Direct questions receive direct answers. For example, 'Do you use this technique?' These kinds of question should, however, be avoided in a semi-structured interview, to give room for flexibility (Turner, 2010).
Indirect Questions	Indirect questions are projective. For example, 'How do you think other members of your team view this technique?'

The types of questions shown in Table 0-2 were used within the context of this study for the semi structured questionnaire. The preliminary stages outlined above for building the semi structured interview questionnaire also followed the guide by Kallio et al. (2016).

IV. Appendix D: Interview Consent Form

Department of Information Systems
Leslie Commerce Building
Engineering Mall, Upper Campus
OR
Private Bag X3 - Rondebosch - 7701
Tel: +27 (0) 21 650 2261 Fax: +27 (0) 21650 2280
Internet: http://www.commerce.uct.ac.za/informationsystems/

Request to conduct research and interview participation consent form.

Dear Sir/Madam,

In terms of the requirements for completing a master's degree in information systems at the University of Cape Town a research study is required. The researcher, in this case David Akobe, has chosen to conduct a case study entitled "*The application of deep learning models and machine learning algorithms in business intelligence for business optimisation*". The objective of the research is to understand how business analyst/professionals apply deep learning models and machine learning algorithms in their organisation to deal with vast amounts of data for the purpose of business optimisation.

This research has been approved by the Commerce Faculty Ethics Committee. Your participation in this research is voluntary. All information will be treated in a confidential manner and used exclusively for the purpose of this study. No individual names will be recorded or published. You will not be requested to supply any identifiable information, ensuring anonymity of your responses. You can choose to withdraw from the research at any time for whatever reason, in accordance with ethical research requirements.

The data collection method will be one-on-one interviews with the business analysts/professionals in the business intelligence/data analytics department. The interviews will be conducted at your place of business or a place convenient to you and will last for about 45 minutes. If you are willing to participate in this study, kindly sign the attached form and return to me at your earliest convenience. Should you have any questions regarding this research, please feel free to contact me on +234 8102599098 or email: akbdav001@myuct.ac.za

Your participation in this study would be greatly appreciated but is entirely voluntary.

Sincerely,

Akobe David

Signed by candidate

Researcher \ M. Com Student, (UCT)

Department of Information Systems

University of Cape Town

Email: akbdav001@myuct.ac.za

Dr. Sumarie Roodt

Research Supervisor

Department of Information Systems

University of Cape Town

Email: sumarie.roodt@uct.ac.za

Research Participant Consent Form

I, ______________________________________, consent to participate in the research on "*The application of deep learning models and machine learning algorithms in business intelligence for business optimisation*".

I am aware that participation is voluntary and that I may choose to withdraw from this study at any time, should I choose to do so.

___________________________ ___________________________

Signature Date

V. Appendix E: Research Instrument

Introductory section (Interviewee profile questions)

Age?

Current role?

Years of career experience?

Years of work experience within the current organisation?

Opening Questions

1. Can you tell me about the current state of business intelligence/Data analytics in your organisation?
    - Follow-up/probing question: What business intelligence or data analytics tools do you currently use in your department?
2. How do you think the rapid growth of customer data has influenced your departmental processes and procedures?

Stage 1: Related to Information processing needs.

3. What kind of structured and/or unstructured customer datasets do you use with in your department?
4. What specific customer needs prompted/influenced your decision to adopt and use artificial intelligence techniques?

Stage 2: Related to information processing capabilities.

5. What does your role in the department entail and what are your responsibilities and expertise?
6. What are the types of machine learning algorithms currently employed in your department?
7. What are the types of deep learning models currently employed in your department?
8. In what areas do you use the aforementioned artificial intelligence techniques for customer retention?
9. In what areas do you use the aforementioned artificial intelligence techniques for customer satisfaction?

10. Can you tell me about some of the AI driven capabilities that you have added to your customer banking platforms to help improve your customer relationship management?
11. What type of customer data does your department analyse using machine learning algorithms?
    - Follow-up: Could you briefly define each algorithm and state the data type for which it is applicable?
12. What type of customer data does your department analyse using deep learning models?
    - Follow-up: Could you briefly define each model and state the data type it is applicable for?
13. What additional resources and/or skillsets did you have to employ to make efficient use of AI technologies in your department?

Stage 3: Related to the 'fit' concept

14. How do you determine the right algorithm or model to use for a certain data analysis task?
15. Can you explain the steps you take when using any of the aforementioned algorithms or models to analyse customer data for the purpose of customer retention?
16. Can you explain the steps you take when using any of the aforementioned algorithms or models to analyse customer data for the purpose of customer satisfaction?
17. Can you briefly explain other uses of AI technologies in your department and the benefits you obtain from them in terms of business optimisation?
18. Would any of the aforementioned benefits be obtained if only business intelligence tools were used, without the addition of deep learning and/or machine learning algorithms?
19. Would you say that the benefits of these adopted technologies outweigh the cost of employing them?

VI. APPENDIX F: Respondents Profile

Table 0-3: Respondents Profile

Pseudonym	Age (years)	Role	Career experience (years)	Bank
Respondent 1	28	Data Scientist	7	A
Respondent 2	27	Data Scientist	5	A
Respondent 3	28	Data Scientist	4	A
Respondent 4	24	Data Scientist	2	A
Respondent 5	28	Data Engineer	2	A
Respondent 6	25-30	Business Intelligence Analyst/ Developer	5	A
Respondent 7	31	Data Quality and Governance specialist	4	B
Respondent 8	28	Data Scientist	4	B
Respondent 9	27	Data Scientist	3	B
Respondent 10	36	Data Scientist	8	B
Respondent 11	42	Data analyst/ Visualisation Expert	12	B
Respondent 12	32	Data Scientist	9	B
Respondent 13	34	Data Analyst	7	B
Respondent 14	31	Data Scientist	4	C
Respondent 15	28	Data Analyst	3	C
Respondent 16	21	Data Scientist	3	C
Respondent 17	28	Data/Automation Engineer	4	C
Respondent 18	25	Data Scientist	2	C
Respondent 19	29	Data /Analyst	2	C
Respondent 20	30 - 35	Data Engineer	6	C

VII. Appendix G: Pilot Test Results

The pilot test was carried out to determine whether the questions were clearly articulated and would be easy to understand to obtain the required response from prospective respondents. The research instrument was tested with four professionals: two business analysts, an electrical engineer with a deep understanding of artificial intelligence, and a master's student. The views of the pilot study respondents are shown in Table 0-4.

Table 0-4: views of pilot study respondents

Pilot study respondents	Response
Business analyst one	"The questions are fine and okay."
Business analyst two	"This is good and well put together. You have used the conventional analytics vocabulary".
Electrical Engineer	"I understand all the questions. You can also add some other technical words such as 'use case".
Master's student	"The questions are fine. However, can you rephrase the question that says, 'What is your view of the rapid growth of customer data in the 21st century and its influence on the business environment?' to 'How has the rapid growth of customer data influenced the business environment and decision-making processes?' I think the rapid growth is clear, so you do not need to ask what their view on rapid growth is."

The views of the pilot study respondents were considered, and adequate changes were made to the research instrument where necessary.

VIII. Appendix H: Interview procedure

Table 0-5: Interview procedure

Interview Procedure
Pre-Interview Stage
• Study the interview questions and consent form. • Send out the consent forms and ethics approval forms to the interviewees. • Send out a short brief of your research study and the interview questions to the interviewee, so that they are fully informed about the process. • Confirm the date, time and location of the interview. • Cross-check the recording equipment and ensure that the note taking materials are present. • Arrive promptly at the interview location.
Interview Stage
• Greet interviewees warmly and give a brief introduction about yourself. • Briefly explain the purpose and process of the interview. • Ask again for confirmation of consent from the interviewee. • Ask for permission to record the interview section for transcription purposes. • Begin the interview process and ask the questions in the interview guide. • At the end of the interview, give an opportunity for the interviewee to ask questions. • Thank the interviewee and let them know that you will contact them at a later stage for member checking. • Summarise the key points and verify with the interviewee.
Post Interview stage
• Ensure that the interview session was recorded, if it is not, immediately use the notes. • Transcribe the interview within 24 hours after the interview process. • Look at the data to see if they align with the intended outcome of the study. • Make slight changes to the framing of the questions, if need be, to elicit a more in-depth explanation from other interviewees

IX. Appendix I: Ethics approval letter

UNIVERSITY OF CAPE TOWN
IYUNIVESITHI YASEKAPA • UNIVERSITEIT VAN KAAPSTAD

2023/09/02

COM/00403/2023

RE: Research Ethics Committee Project Approval Letter

Dear David Akobe,

Your application for ethics review of your project titled.

The Applications Of Deep Learning Models And Machine Learning Algorithms In Business Intelligence ForBusiness Optimisation.

has been reviewed and evaluated by

the Commerce Research Ethics

Committee.

You may proceed with your research project titled:

The Applications Of Deep Learning Models And Machine Learning Algorithms In Business Intelligence ForBusiness Optimisation.

Please note that should:

(i) any serious or adverse effects to participants occur and/or,

(ii) aspect(s) of your current project change and/or

(iii) any unforeseen events that might affect continued ethical acceptability of the project occur then you should immediately report this to the approving REC. You may be required to submit an amendment to this application, in order to determine whether the changed aspects increase the ethical risks of your project.

Based on the information supplied your application has been successful and is

approved.Please note the following additional conditions associated with this

approval:

(i) * Student may require gatekeeper permission from HR departments of target companies. Student toascertain, in each case (it may vary from organisation to organisation), whether this is required.

Regards,

Commerce Research Ethics Committee.

X. Appendix J: The Nigerian Banking Industry

The Nigerian banking industry has experienced a wave of changes over the years. As far back as 2002, before the use of advanced technological services like the automated teller machine and point of service machines , customers had to always go into banks physically to either deposit or collect money (Benard et al., 2023). However, with the arrival of these technologies and the advent of mobile and online banking, the number of physical visits to the bank has decreased. Customers are now able to send and receive money and perform various other bank transactions simply with their mobile phones (Benard et al., 2023).

The banking industry in Nigeria experienced its first reformation in 1952. This brought about certain rules and guidelines for the supervision of banks. Universal banking guidelines followed suit in 2001, and four years later, commercial banks in Nigeria were reduced from 89 to 24 (Ogunleye, 2021). In 2009, five commercial banks that lacked adequate capital for sustainability were merged with other existing banks that were deemed robust enough to acquire them. This led to a total of 19 commercial banks in Nigeria (Ogunleye, 2021). These reforms were carried out by the governing and regulatory body for the banking system in Nigeria, known as the CBN, in a bid to ensure stability and create a stronger banking system (Ogunleye, 2021).

In 2017, the CBN reported that the ATM was the most used electronic payment transaction method, accounting for 78.2%, it was closely followed by the POS machine, which represented 14.3%. Mobile payments and web payments accounted for 4.7% and 2.8% respectively (Ohiani, 2020). The 21st century technologies have helped to improve the overall baking experience in Nigeria. ATMs, debit cards, mobile banking, e-data, and much more, now make it possible for customers to make various payments from the comfort of their homes (Ohiani, 2020).

The Nigerian banking industry has predominantly operated in a cash-based society over the years, even with the arrival of various technological systems. Branch offices of commercial banks still entertain customers who regularly come to deposit or withdraw money (Ogunleye, 2021). Many customers still face a myriad of issues with ATM and POS machines, and the adoption of these technologies in the baking industry is still limited. Therefore, customers queue up daily to lay complaints at the branch offices of commercial banks (Ogunleye, 2021). The CBN has tried on several occasions to introduce a cashless policy in the Nigerian society. The first attempt was made in 2012 (Monye, 2023), with the aim of reducing the Naira notes used for transactions. The cashless policy at that time was projected to help in the following areas: (1) Reduce the cost of providing banking services. (2) Help the CBN manage the economy and ensure the sustainability of the monetary policy. The projected benefits for customers were a reduction in cash-related crimes, and easier access to banking services. For Cooperations, it meant expedited access to capital and reduction in cost related to cash handling. Lastly, for the government, it would lead to increase in tax collection and economic development. The key terms of the policy were a new cash handling charge on daily withdrawals or cash deposits exceeding 500,000 Naira for individuals and three million for cooperate organisations (Monye, 2023). The efforts of the CBN proved unsuccessful, as the Nigerian society was not prepared for the new policy. Banking systems lacked the required payment infrastructure and digital platform to handle the growing number of online transactions (Monye, 2023). This inevitably led to the suspension of the policy, and further attempts to rekindle the policy in 2017 were also brought to a halt. This was done to allow for the expansion of the financial sector in Nigeria and for the adoption of alternative payment methods and payment platforms (Monye, 2023).

In 2022, CBN began the Naira redesign policy and reintroduced new cash withdrawal limits. The new naira notes were launched on November 23, 2022. New Naira notes for 200, 500 and 1000 naira were produced (Monye, 2023). To facilitate the circulation of the new notes, CBN introduced a cash swap policy, that enabled customers to exchange the old naira notes, for the new ones, by going directly to banks, or CBN itself for the exchange. This new cashless policy led to a withdrawal limit of 500 thousand naira a week for individuals and five million naira for corporate organisations over the counter. There was also a withdrawal limit of twenty thousand naira daily and hundred thousand naira weekly for individuals (Monye, 2023). This new cashless policy is projected to further stabilise the financial sector in Nigeria and introduce a more improved economy for small and medium enterprises. It is also projected to bring in cost savings by reducing the cost of building bank branches and ATM galleries, with the banking system going fully digital. The new cashless policy could also help with crime reduction, as with digital transactions there is evidence of an audit trail for easy investigation (Monye, 2023). Despite these projected benefits however, the financial sector in Nigeria still struggles with some challenges due to the cashless policy. There still lies the old problem of inadequate payment infrastructure and the lingering preference for cash by the mases in the Nigerian society (Monye, 2023).

Table 0-6 shows the list of commercial banks in Nigeria.

Table 0-6: List of Commercial banks in Nigeria (Bernard et al., 2023)

S/N	Bank name
1	Access Bank
2	Citi Bank
3	Ecobank
4	First Bank
5	Fidelity Bank
6	First City Monument Bank
7	Guaranty Trust Bank
8	Heritage Bank
9	Keystone Bank
10	Polaris Bank
11	Providus Bank
12	Sterling Bank
13	Stanbic IBTC
14	Standard Chartered Bank
15	United Bank of Africa
16	Unity Bank
17	Union Bank
18	Wema Bank
19	Zenith Bank

XI. Appendix K: The Nigerian Context

Nigeria is a country located on the western coast of the African continent and is home to over two hundred and thirty-three million people, consisting of about 250 ethnic groups and 36 states (Britannica, 2023). Of these 36 states, Lagos State is classified as the sixth megacity in the world, boasting a population of over 10 million. Lagos state is also known as Nigeria's financial hub, with major banks and top organisations in the country all having their headquarters in the city of Lagos (Britannica, 2023).

XII. Appendix L: Documents reviewed

Online reports were reviewed as supplementary materials in addition to the primary data collection method for this study. These reports provided more information about the Nigerian banking industry and the data protection laws in place for the protection of customer data.

Documentary review is beneficial in qualitative research and involves reviewing various types of documents, institutional reports, and texts, to understand a situation (Morgan, 2022). The supplementary documents reviewed for this study are shown in Table 0-7.

Table 0-7: Documents reviewed for this study

Document	Description	Source
Data protection laws of the world Nigeria	Report on the data protection laws in Nigeria	https://www.dataguidance.com/notes/nigeria-data-protection-overview
Nigeria - Data Protection in the Financial Sector	Data protection act legislature	https://www.aelex.com/wp-content/uploads/2019/12/Nigeria-Data-Protection-in-the-Financial-Sector-_-DataGuidance.pdf
Why The Central Bank of Nigeria made the Cashless Policy.	Report on why the cashless policy in Nigeria started	https://www.cbn.gov.ng/

XIII. Appendix M: Correspondence with the head of departments in banks

AI Product Manager – Bank A

Good afternoon, [redacted]. I was referred to you by my friend. Thank you for sharing your LinkedIn contact. As [redacted] probably mentioned, I am currently undergoing a master's degree in information systems at the University of Cape Town, and my dissertation topic is 'The application of deep learning models and machine learning algorithms in business intelligence for business optimisation'. My study is largely qualitative and would involve interviewing professionals in the banking business intelligence or data analytics department. After consulting the past literature on the application of DL and ML techniques in organisations in Nigeria, I found that banks are more likely to use these techniques. That is why I asked my friend [redacted], who then contacted you. My research instrument will be semi-structured interviews with analytics or business intelligence department members to discover their lived experiences and how they use machine learning algorithms and/or deep learning models for tasks such as sentiment analysis for customer retention and relationships and tasks such as sales forecasting, etc. I wanted to know if You and your team at Wema Bank kind would be enough to grant me the opportunity to do this. I am still working on my research design and instrument. Still, once I am done and have gotten the necessary ethics approval from my university, I can reach out to you once more and start the formal process if you are open to it. Thank you once more for agreeing to hear me out.

Reply

Hi David, thanks for reaching out. Your research is interesting. I am happy to share my experiences with you. I should also be able to ask colleagues to share their experiences. How long would the research likely last for? You can always message me whenever you get the green light on your project. Cheers

Head of The Business Intelligence Department – Bank B

Good afternoon, [redacted].

Many thanks for availing your email address.

I tried to send this with my school mail, but it wasn't delivered. for reference, my school mail address is AKBDAV001@myuct.ac.za
I am David Akobe, a postgraduate student at the Faculty of Commerce at the University of Cape Town. I am currently studying in the Department of Information Systems.
My research focuses on the current state and applications of deep learning models and machine learning algorithms in Nigeria.

From my study of past literature, I discovered that the banking industry in Nigeria represents one of the early adopters of business and artificial intelligence. Hence, I believe you and your team at Stanbic will provide invaluable insight into my study. I would like, therefore, to kindly ask if it would be possible to have interview sessions with you and your team to find out how they use Deep learning models and Machine Learning algorithms for business optimisation. Your experiences and those of your staff members will help shed more light on the current state of deep

learning and machine learning algorithms in Nigeria. They will contribute immensely to the body of research and scarce literature on using DL models and ML techniques in Nigeria. I understand the private nature of the banking systems, so the questions will not require you or any of your team members to disclose any information about private internal processes. I will ask "How do you define machine learning algorithms?" and "What kind of data do you use machine learning algorithms to analyse?" etc. The major goal of asking these questions will be to understand the experiences of staff members in the department and to understand what DL models or ML techniques they use and the benefits they get from those models and algorithms to contribute to the scarce literature on the current state of artificial intelligence technologies in Nigeria. The interviews will be 30-45 minutes for each individual. I am still working on my research design now. But once I am done and have gotten the necessary ethics approval from my university. I can contact you again to formalise the process and schedule the interviews if you are open.
Many thanks once again for the opportunity to explain.

Kind regards.

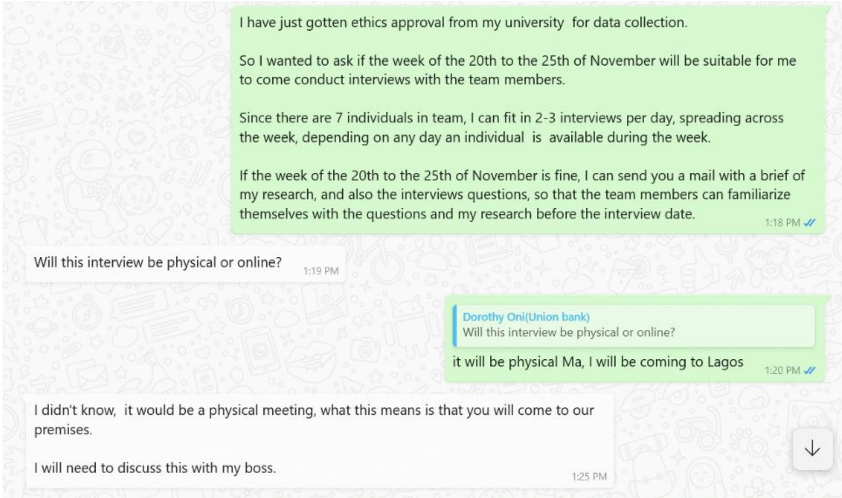
Reply
Hello David,
This is to inform you that you can come to conduct the interview with my team anytime you are ready.
Kindly give me a week's notice before the chosen date.

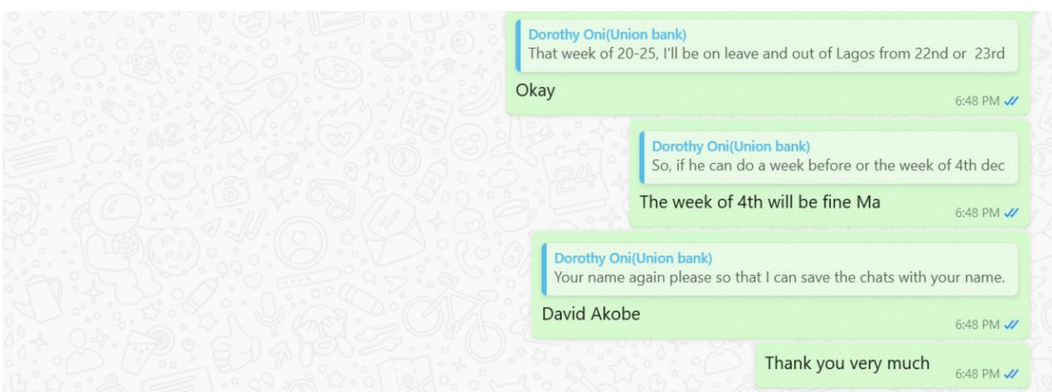
Best regards,

[redacted]

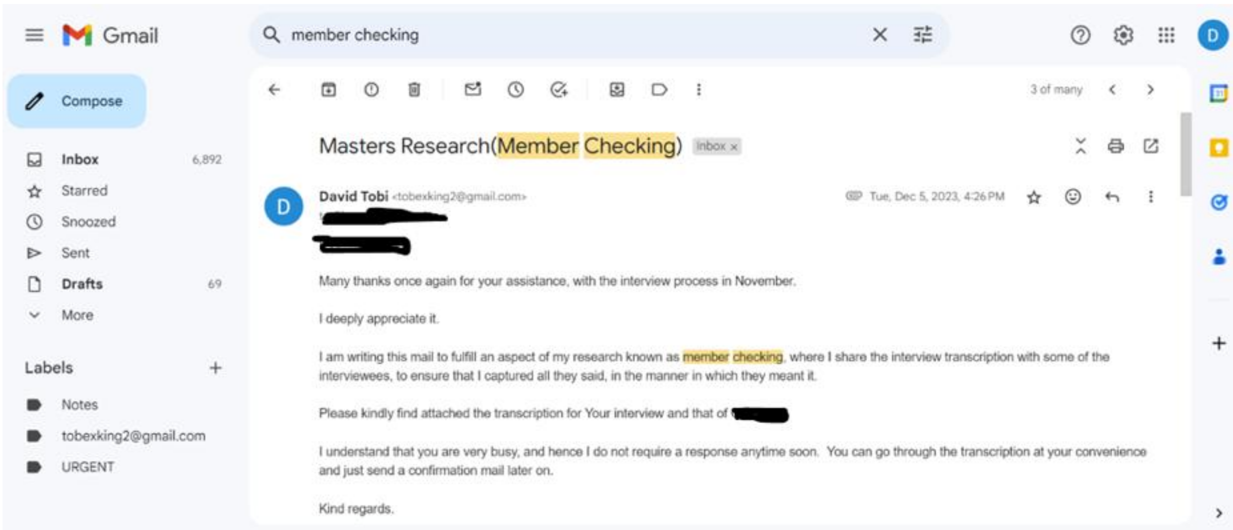
Head, Data and Analytics / Engineering

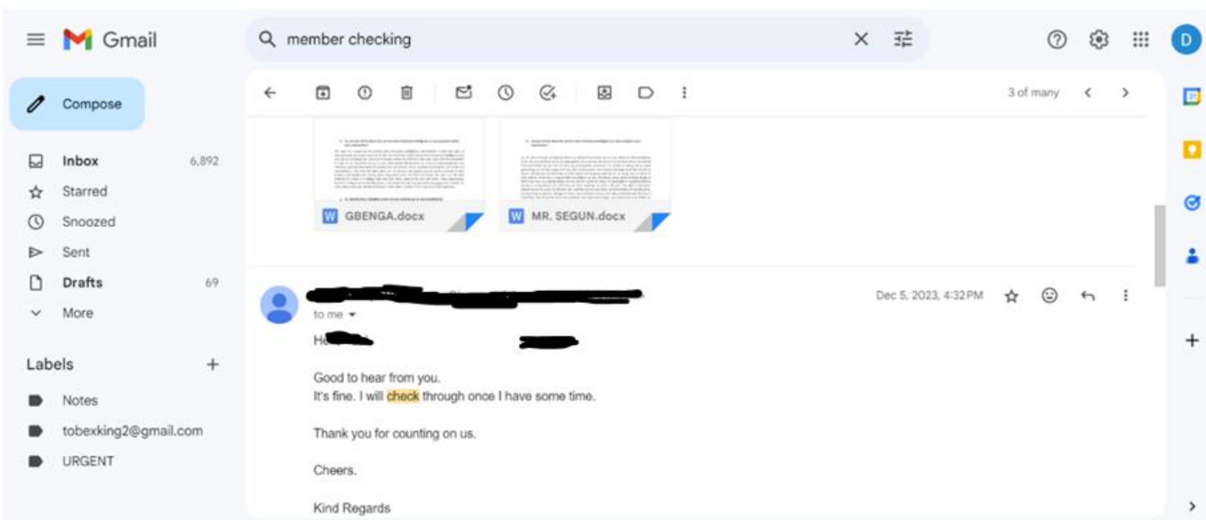
Head Of Business Intelligence Department – Bank C

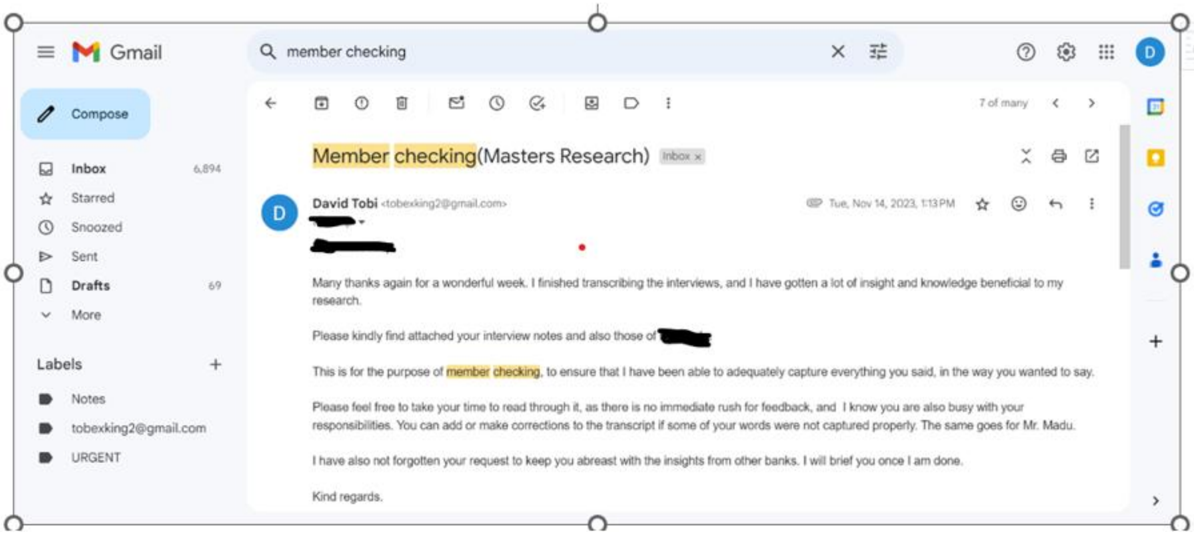




XI. Appendix N: Member checking with the head of departments for Bank B and Bank A







member checking

Member checking(Masters Research) Inbox

David Tobi <tobexking2@gmail.com> Tue, Nov 14, 2023, 1:13 PM

[redacted]

[redacted]

Many thanks again for a wonderful week. I finished transcribing the interviews, and I have gotten a lot of insight and knowledge beneficial to my research.

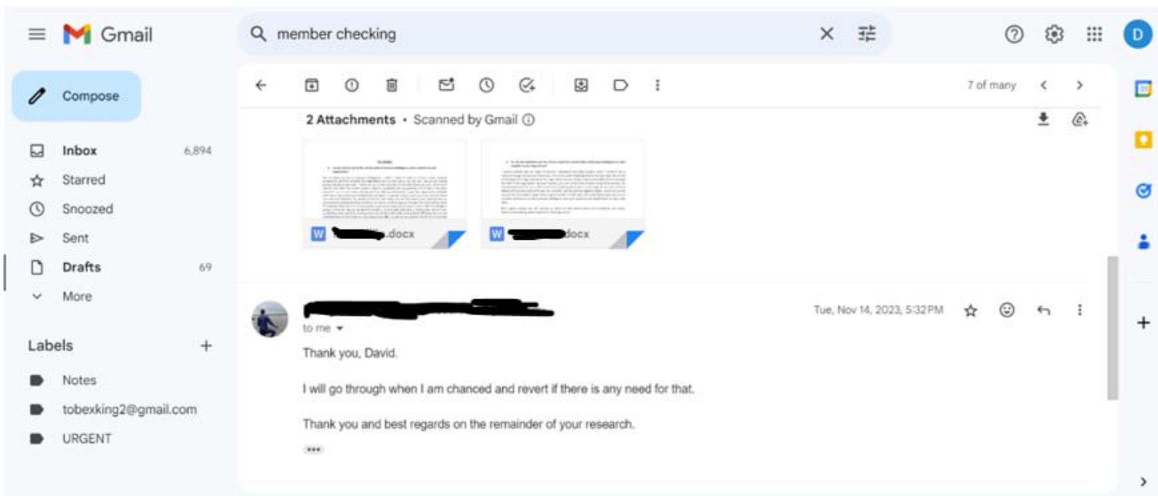
Please kindly find attached your interview notes and also those of [redacted]

This is for the purpose of member checking, to ensure that I have been able to adequately capture everything you said, in the way you wanted to say.

Please feel free to take your time to read through it, as there is no immediate rush for feedback, and I know you are also busy with your responsibilities. You can add or make corrections to the transcript if some of your words were not captured properly. The same goes for Mr. Madu.

I have also not forgotten your request to keep you abreast with the insights from other banks. I will brief you once I am done.

Kind regards.



member checking

2 Attachments • Scanned by Gmail

[redacted].docx

[redacted]docx

[redacted] Tue, Nov 14, 2023, 5:32 PM

to me

Thank you, David.

I will go through when I am chanced and revert if there is any need for that.

Thank you and best regards on the remainder of your research.