THE ROLE OF ARTIFICIAL INTELLIGENCE ON FIRM FINANCIAL PERFORMANCE

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BEING A PROJECT SUBMITTED TO THE DEPARTMENT OF ACCOUNTING, FACULTY OF MANAGEMENT SCIENCES, UNIVERSITY OF BENIN, BENIN CITY IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF SCIENCE (B.Sc.) DEGREE IN ACCOUNTING.

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DECLARATION

I declare that:

This thesis is based on a study undertaken by me in the department of Accounting, Faculty of Management Sciences, University of Benin, Benin City, under the supervision of Prof. C.O. Mgbame of the department of Accounting, Faculty of Management Sciences, University of Benin, Benin City Nigeria. This work has not been submitted for the award of any degree elsewhere. All ideas and views are produced of my personal research and where the views of others have been expressed, they have been dully acknowledged. I shall totally, wholly and fully be responsible for the liability that may flow from this study if any.

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DOWELL GIFT OYINPRESIDOR

CERTIFICATION

This is to certify that the project "The role of Artificial Intelligence on firm financial performance" was carried out by Dowell Gift Oyinpresidor with Matriculation Number MGS2104529. It has been read and recommended for acceptance in partial fulfilment of the award of the Bachelor of Science (B.Sc) in Accounting.

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DEDICATION

This work is dedicated to the almighty God who made me all I'm and granted me the strength, wisdom and knowledge needed to carry out this work. I also specially dedicate this work to my amazing parents, Mr Dowell Evinson and Mrs Ezonebi Dowell and my siblings for always believing in me and pushing me to be my best in my academic pursuit.

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ABSTRACT

The board objective of this study is to examine the role of artificial intelligence on firm financial performance. Specifically, this study investigated the effects chatbot applications, robotic process automation and AI application on firm financial performance.

The study used a primary data collected from 50 employees of the commercial banks within Ugbowo, Benin city, Edo State. Various statistical and econometric tool were applied to analyze the data. The results revealed that chatbot applications have a positive and statistically significant impact on organization performance. Robotic process automation and AI application in decision making have a positive but statistically insignificant impact on organization performance

Based on the findings, the study recommended that businesses should consider increasing their investment in chatbot technologies, Organizations should reassess the effectiveness of their RPA strategies and business should explore other AI areas like predictive analytics, customer insights, or process automation

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Artificial Intelligence (AI) has evolved rapidly in recent years, revolutionizing industries worldwide by enhancing business processes, improving decision-making, and increasing operational efficiency. In the context of Nigeria, AI presents significant opportunities for firms to gain a competitive edge, especially as the country's digital economy grows and innovation accelerates. According to Brynjolfsson and McAfee (2014), AI technologies, such as machine learning, data analytics, and automation, have proven effective in transforming firms' performance across various sectors by streamlining operations, improving customer experience, and facilitating data-driven strategies.

In Nigeria, the adoption of AI technologies remains relatively new, but there is increasing interest and investment, particularly among tech startups, financial institutions, and e-commerce platforms (Adewale & Ezeani, 2022). The Nigerian business environment, characterized by challenges such as inconsistent infrastructure, regulatory gaps, and a highly competitive market, makes it crucial for firms to explore innovative solutions that can enhance productivity and overall performance. AI, as a tool for data analysis and process automation, holds the potential to drive growth in both established corporations and new businesses in sectors such as banking, agriculture, manufacturing, and telecommunications (Omotayo, 2021). While AI offers transformative opportunities, the application of such technologies in Nigeria is not without challenges. Firms often face difficulties in integrating AI into their existing systems due to the high cost of AI technologies and the lack of a skilled workforce (Adebayo, 2023). Additionally, Nigeria’s digital infrastructure, which is still in the developmental stage, poses constraints in harnessing the full potential of AI (Adewale & Ezeani, 2022). Despite these hurdles, firms in sectors like banking and telecommunications have begun leveraging AI for customer service automation, fraud detection, and predictive analytics, which have led to measurable improvements in operational efficiency and customer satisfaction (Ogunyemi et al., 2022).

Furthermore, AI adoption in Nigeria offers significant potential for agricultural firms, where technologies like machine learning and robotics can help optimize crop yields and reduce waste. AI-driven solutions in agriculture can address some of the country’s pressing challenges, such as food security and the inefficiencies of traditional farming methods (Omotayo, 2021). In the manufacturing sector, AI has the potential to reduce production costs, improve supply chain management, and enhance product quality by providing firms with real-time data and insights into their operations (Adebayo, 2023). The integration of AI also holds the promise of driving Nigeria's economic diversification by supporting emerging sectors like fintech, e-commerce, and healthtech, which are increasingly reliant on data analytics and automated systems for innovation. Research by Choi et al. (2018) suggests that AI-powered solutions enable firms to identify new business models, optimize resource allocation, and increase profitability in competitive environments. As AI continues to develop in Nigeria, it is expected that the technology will play a crucial role in reshaping the way businesses operate, ultimately contributing to the country's overall economic growth.

This study seeks to explore the effect of artificial intelligence on firm financial performance in Nigeria. By examining the experiences of Nigerian firms across various sectors, the study will provide valuable insights into how AI technologies can enhance firm performance and contribute to long-term business sustainability in the Nigerian market.

1.2 Problem of the study

Despite the increasing global adoption of Artificial Intelligence (AI) and its transformative impact on firm financial performance, the application of AI in Nigerian firms remains under-researched and underutilized. In Nigeria, while there is growing interest in AI, particularly among startups and large corporations in sectors like banking, telecommunications, and agriculture, many businesses face substantial barriers to its effective implementation. These challenges include high implementation costs, a lack of skilled workforce, inadequate digital infrastructure, and insufficient regulatory frameworks (Adebayo, 2023; Adewale & Ezeani, 2022). As a result, many Nigerian firms have not fully harnessed the potential of AI to enhance operational efficiency, improve decision-making processes, and gain a competitive advantage (Omotayo, 2021).

Moreover, while the potential benefits of AI adoption, such as improved customer service, cost reduction, and innovation, have been documented globally, there is limited empirical research on how these factors specifically affect firm performance in Nigerian (Brynjolfsson & McAfee, 2014). This knowledge gap is compounded by the unique socio-economic challenges faced by Nigerian businesses, which may influence the outcomes of AI adoption differently than in more developed markets. For instance, Nigeria's infrastructural limitations and high costs of AI technologies present significant obstacles that may affect the results of AI adoption when compared to other countries with more advanced technological ecosystems (Adebayo, 2023; Ogunyemi et al., 2022). This study seeks to address this gap by exploring the effect of AI on firm financial performance in Nigeria.

1.3 Research Questions

The problem stated above resulted in the formulation of the following questions.

1. What is the impact of chatbot applications in business on firm financial performance?
2. What is the effect of robotic process automation on firm financial performance?
3. What is the impact of AI applications in decision-making on firm financial performance?

1.4 Objectives of the Study

The primary objective is to investigate the impact of artificial intelligence on firm financial performance. Its specific objectives are to:

1. examine the impact of chatbot applications in business on firm financial performance;
2. investigate the effect of robotic process automation on firm financial performance; and
3. assess the impact of AI applications in decision-making on firm financial performance.

1.5 Research Hypotheses

This study aims to examine the impact of artificial intelligence on firm financial performance. Therefore, the research hypothesis for this study is as follows:

H_1: Chatbot application in business has no significant impact on firm's financial performance.

H_2: Robotic process automation has no significant effect on firm financial performance.

H_3: Artificial Intelligence application in decision making has no significant impact on firm financial performance.

1.6 Scope of the Study

This study aims to examine the impact of artificial intelligence on firm financial performance. It is believed that the introduction of artificial intelligence in organizations will reduce staff workload and increase efficiency. To achieve its stated objectives, the study will focus on employees of organizations as the primary source of relevant data. Specifically, the study will target employees of banks within Ugbowo, Benin City, Edo State. The employee in charge of customer care services and marketing/ digital marketing of the banks will be considered because of the impact the independent variable considered plays in their duties. The population for this study will consist of employees from Banks in Ugbowo, from which a sample of 50 employees will be selected. Banks in Ugbowo have been chosen to facilitate easy access to the study's data collection. The data required for analysis will be collected through a well-structured questionnaire administered by the researcher.

1.7 Significance of the Study

The findings of this study are significant to both internal and external stakeholders of organizations in the following ways:

1. Firm Executives: The findings of this study will provide insights into how AI can be strategically integrated to optimize firm performance, leading to improved decision-making, increased efficiency, and competitive advantage. Business leaders can use the

findings to drive innovation, enhance operational performance, and identify key areas where AI can contribute to organizational growth and profitability.

2. Employees: Organization employees will benefit from the findings if this study because it will enable them to understand how AI can support and augment their roles, increase productivity, and enable them to focus on more complex, value-adding tasks.
3. Consumers: This study offer consumers an insights into how AI adoption by firms can enhance their overall experience through improved customer service, personalized offerings, and better product or service quality.
4. Academia/Researchers: The findings from this study contribute to the existing body of knowledge on AI's role in firm financial performance. Researchers can build on this work to explore further areas such as AI adoption barriers, industry-specific applications, and the long-term effects of AI on employee roles and business models.

1.8 Limitation of the study.

The main limitation of the study is it focus on only the banking sector on the economy. Artificial intelligence can be applied almost all sectors of the economy. However, this study focus mainly on the effect of artificial intelligence on the banking activities leaving other sectors of the economy untouched.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter goes into detail discussion of related ideas and reviewing relevant theories because it relates to the current topic. This study will look into relevant prior studies of many academics and researchers. The chapter will therefore be divided into four major sections which will include: introduction, conceptual framework, empirical review and theoretical review.

2.1 Conceptual Review

2.1.1 Concept of Firm Financial Performance

Firm performance is a critical subject in business research, as it directly correlates with the sustainability and growth of firms. Firm performance can be defined in a broad sense as the extent to which a company achieves its financial and operational objectives. It is a multifaceted concept encompassing various measures, such as profitability, productivity, market share, and shareholder wealth (Hussain et al., 2020). Understanding the factors that affect Firm performance is crucial for stakeholders, including managers, investors, policymakers, and academic researchers. Firm performance is commonly defined through two major categories: financial performance and non-financial performance.

Financial performance is often assessed using financial ratios derived from the firm's financial statements. Key metrics include profitability (measured by net profit margin, return on assets [ROA], and return on equity [ROE]), liquidity (current and quick ratios), efficiency (asset turnover), and solvency (debt-to-equity ratio) (Sharma & Kesari, 2021). These indicators help in understanding the firm's ability to generate earnings, manage costs, and meet financial obligations. According to McWilliams and Siegel (2000), financial performance is a direct reflection of management effectiveness, resource allocation, and external market conditions. For example, Firms with higher profitability and efficient cost management are generally able to achieve higher returns, which is an indicator of superior financial performance (Nguyen et al., 2021). Furthermore, financial performance metrics are crucial for assessing the overall health and operational success of an firm, as they provide quantifiable insights into a firm's ability to create value for shareholders.

Non-financial performance measures the firm's intangible assets, such as customer satisfaction, employee morale, brand reputation, and innovation capacity. For instance, a company may exhibit high profitability yet struggle with customer retention or employee turnover, which can ultimately hinder long-term success (Amah & Okafor, 2020). Non-financial performance is increasingly recognized as an essential aspect of a firm's long-term success, with intangible factors often providing a competitive advantage that financial measures alone may overlook. The balanced scorecard, developed by Kaplan and Norton (1992), is a popular framework used to assess non-financial aspects of performance. It incorporates four perspectives: financial, customer, internal processes, and learning and growth. According to the balanced scorecard model, non-financial performance metrics are equally important as financial ones in predicting a firm's future success, as they offer a more holistic view of an firm's capacity to innovate and adapt to changing market conditions (Chong, 2021).

Determinants of Firms Performance

Firm performance is influenced by a wide array of factors that can be categorized into internal and external determinants.

Internal Determinants

Corporate Governance: The effectiveness of a firm's corporate governance structure plays a significant role in determining its performance. Strong corporate governance mechanisms, such as board independence, shareholder rights, and managerial accountability, are crucial for fostering better decision-making, transparency, and overall financial performance. Research has shown that firms with well-structured governance systems tend to outperform their peers, as these structures help mitigate agency problems, align management's interests with shareholders, and promote ethical practices (Adams & Ferreira, 2009; Bhagat & Bolton, 2013).

Leadership and Management: The quality of leadership within a firm has a direct impact on its performance. Effective leadership involves making strategic decisions, managing resources efficiently, and inspiring employees to achieve formal goals. Transformational leadership, in particular, is often linked to superior firm performance, as it encourages innovation, fosters adaptability, and motivates employees to perform beyond expectations (Bass & Avolio, 1994; Tichy & Devanna, 2015).

Human Capital: The skills, knowledge, and experience of a firm’s employees—remains a crucial determinant of firm performance. Firms that prioritize the development of human capital through training, skill enhancement, and continuous professional development are more likely to achieve superior performance outcomes (Gagne et al., 2015). Firms that invest in their employees’ growth and provide opportunities for advancement tend to see increased employee satisfaction, higher productivity, and lower turnover rates, all of which positively influence firm performance (Lepak & Shaw, 2008).

Innovation and R&D: Innovation and research and development (R&D) are critical drivers of competitive advantage in today's rapidly evolving business environment. Companies that consistently invest in R&D and prioritize innovation in products, services, and processes tend to outperform competitors in the long run (Teece, 2010). Investments in R&D enable firms to create new products, enhance existing offerings, and improve operational efficiency, all of which contribute to increased market share, customer satisfaction, and revenue growth (Chesbrough, 2003).

External Determinants

Market Competition: Market competition plays a significant role in shaping a firm's performance. In highly competitive environments, firms must continuously innovate and improve their operational efficiency to maintain or grow their market position. Industries characterized by low barriers to entry and intense rivalry tend to create a challenging environment for firms, as they must constantly adapt to survive and remain profitable. In such competitive markets, firms that fail to innovate or improve productivity may lose market share, resulting in declining profitability and diminished competitiveness (Teece, 2010).

Economic Conditions: Macroeconomic factors, such as inflation, interest rates, and overall economic growth, can significantly impact firm performance. In periods of economic growth, firms may experience higher consumer demand, increased revenues, and more favorable market conditions. However, in times of economic downturns, firms may face declining revenues, reduced consumer spending, and higher operational costs (Kotler et al., 2015). In particular, inflation can increase the costs of raw materials and labor, while high interest rates can raise borrowing costs for businesses, potentially affecting their ability to expand or invest in new opportunities (Gertler & Gilchrist, 2019).

Regulatory Environment: The regulatory environment in which a firm operates can profoundly affect its ability to perform. Changes in tax policies, labor laws, and environmental regulations can either create opportunities or impose significant challenges on firms. For example, regulatory changes that lower tax rates or reduce compliance burdens can stimulate business growth and increase profitability (Klapper & Love, 2004). Conversely, stricter regulations may increase costs or require firms to alter their operations, impacting profitability. The ability of firms to navigate regulatory environments and comply with applicable laws is essential for ensuring sustained performance (Bebchuk & Weisbach, 2010).

Measuring Firm Performance

Several methods are employed to measure formal performance, each focusing on different aspects of the firm's operations. The most common methods include:

Financial Ratios: As mentioned earlier, financial ratios are among the most widely used metrics for assessing firm performance. These include profitability ratios, liquidity ratios, and efficiency ratios, which provide insights into how well a company is performing financially.

Profitability can be measured mainly through the following performance measures: return on assets, return on equity and return on investment.

Return on Equity: The return on equity (ROE) is a measure of the profitability of a business in relation to its equity (Jason, 2023). Return on equity measures how many naira of profit is generated for each naira of shareholder's equity and also measures how well the company utilizes its equity to generate profits. ROE is especially used for comparing the performance of companies in the same industry. As with return on capital, a ROE is a measure of management's ability to generate income from the equity available to it. ROEs of 15–20% are generally considered good (Loth, 2022).

Return on Assets: Return on assets (ROA) shows the percentage of how profitable a company's assets are in generating revenue (Crossom et al., 2008). Return on assets tells what the company can do with what it has, i.e. how many naira of earnings they derive from each naira of assets they control. It's a useful number for comparing competing companies in the same industry. The number will vary widely across different industries. Return on assets gives an indication of the capital intensity of the company, which will depend on the industry; companies that require large initial investments will generally have lower return on assets. ROAs over 5% are generally considered good.

Return on Investment: This is a ratio between net income (over a period) and investment (costs resulting from an investment of some resources at a point in time). A high ROI means the investment's gains compare favourably to its cost. As a performance measure, return on investment is used to evaluate the efficiency of an investment or to compare the efficiencies of several different investments (Jason, 2023). In business, the purpose of the return on investment (ROI) metric is to measure, per period, rates of return on money invested in an economic entity in order to decide whether or not to undertake an investment. It is also used as an indicator to compare different investments within a portfolio. The investment with the largest ROI is usually prioritized, even though the spread of ROI over the time period of an investment should also be taken into account. Return on investment can be calculated in different ways depending on the goal and application**.**

Market-Based Measures: Market-based performance measures, such as stock prices, market share, and price-to-earnings ratios, provide an external perspective on a firm's performance. These indicators reflect how investors perceive a firm's future growth potential. For example, rising stock prices typically signal investor confidence, while declining prices may indicate concerns about profitability (Fama & French, 2015). Market share, likewise, indicates a firm's competitive strength, with larger shares often correlating with higher profitability (Santos & Brito, 2012). However, these measures can be volatile, influenced by external factors such as economic conditions.

Employee and Customer Satisfaction: Non-financial indicators like employee satisfaction, customer loyalty, and brand equity are increasingly used to assess long-term performance. Research shows these factors often predict future financial success (Harter et al., 2002). Satisfied employees tend to be more productive and contribute to a positive firm culture (Wright & Cropanzano, 2013). Similarly, high customer satisfaction leads to loyalty and repeat business, driving long-term profitability (Anderson et al., 2013). Strong brand equity can also provide a competitive advantage, supporting sustainable growth (Aaker, 2012).

Balanced Scorecard: The balanced scorecard (BSC) is a framework that integrates both financial and non-financial performance measures. It includes four perspectives: financial performance, customer satisfaction, internal processes, and learning and growth (Kaplan & Norton, 1992). The BSC ensures firms focus on long-term strategic objectives, not just shortterm financial results. It helps align a company's strategic goals with day-to-day operations, improving decision-making and overall performance (Kaplan & Norton, 2016).

2.1.2 Artificial Intelligence

Artificial intelligence (AI) refers to the ability of machines, particularly computer systems, to exhibit intelligence similar to that of living beings. It is an area of research within computer science focused on developing methods and software that allow machines to perceive their surroundings and make decisions aimed at achieving specific objectives (Russell & Norvig, 2021). According to Zhang et al. (2020), AI can be seen as the result of leveraging big data and machine learning (ML) technologies to analyze past data and predict future outcomes. Lee & Tajudeen (2020) highlight that AI enables machines to learn from past experiences, adapt to new data, and perform tasks that mimic human behavior. The power of AI lies in its ability to process large amounts of data, which makes patterns more detectable. Chukwudi et al. (2018) explain AI as a system's capacity to perform tasks traditionally carried out by the human brain, including learning, reasoning, understanding relationships, and generating new ideas. Dongre et al. (2020) describe AI as systems programmed to operate on various tasks, enhancing human-like performance through the experimentation and programming of intelligent machines. Similarly, Ezeribe (2019) considers AI as the method by which computers or robots are designed to replicate human thinking processes. Odoh et al. (2018) also define AI as a software system capable of carrying out activities generally performed by the human brain, such as acquiring knowledge and making judgments.

AI, in some views, represents software designed to emulate the expertise and behavior of human professionals, storing human knowledge and experience to solve specific problems, including those in accounting (Stancheva & Todorova, 2018). AI systems can adapt to tasks with minimal human intervention and enhance operational efficiency, as highlighted by Odoh et al. (2018). What sets AI apart from other technologies is its ability to understand its environment and quickly perform tasks that would traditionally require human intelligence (PWC, 2019). This technology is widely utilized across industries, government, and science, with examples such as advanced search engines (e.g., Google), recommendation systems (e.g., YouTube, Amazon, Netflix), voice-activated assistants (e.g., Siri, Alexa), autonomous vehicles (e.g., Waymo), creative tools (e.g., ChatGPT, AI art), and strategic game analysis (e.g., chess, Go) (Google, 2016). The concept of machine intelligence was first explored by Alan Turing, whose research laid the foundation for AI (Copeland, 2004). AI emerged as an academic field in 1956 (Russell, 2021) and went through periods of high expectations and subsequent disillusionment, often referred to as AI winters (Russell & Norvig, 2021). After 2012, with the rise of deep learning, and especially with the advent of transformer architectures in 2017, AI gained considerable momentum, particularly in the United States, leading to the rapid advancements in the field by the early 2020s (Goldman, 2022; Frank, 2023).

In the 21st century, AI's widespread application has been driving a shift toward greater automation, data-driven decisions, and integration into numerous sectors such as healthcare, industry, education, and government. This growing reliance on AI has raised concerns about its long-term impact on job markets, ethical considerations, and the potential risks involved, sparking debates around the need for regulatory frameworks to ensure the technology's safe and beneficial development. AI research is diverse, with sub-fields focusing on specific goals like reasoning, knowledge representation, planning, learning, language processing, perception, and robotics. One of the ultimate aims of AI is achieving general intelligence, where machines can perform any task at the same level as humans (Russell & Norvig, 2021). To achieve these objectives, AI researchers combine techniques from various fields, such as formal logic, neural networks, optimization, and statistics, while also drawing inspiration from psychology, linguistics, philosophy, and neuroscience (Russell & Norvig, 2021).

Goals of Artificial Intelligence

The general problem of simulating (or creating) intelligence has been broken into sub-problems. These consist of particular traits or capabilities that researchers expect an intelligent system to display. The traits described below have received the most attention and cover the scope of AI research (Russell & Norvig (2021).

Reasoning and Problem Solving

Early researchers developed algorithms that imitated step by step reasoning that humans use when they solve puzzles or make logical deductions (Russell & Norvig, 2021). By the late 1980s and 1990s, methods were developed for dealing with uncertain or incomplete information, employing concepts from probability and economics. Many of these algorithms are insufficient for solving large reasoning problems because they experience a "combinatorial explosion": they became exponentially slower as the problems grew larger (Russell & Norvig, 2021). Even humans rarely use the step-by-step deduction that early AI research could model. They solve most of their problems using fast and intuitive judgments.

Knowledge Representation

Knowledge representation and knowledge engineering allow AI programs to answer questions intelligently and make deductions about real-world facts. Formal knowledge representations are used in content-based indexing and retrieval, scene interpretation, clinical decision support, knowledge discovery (mining "interesting" and actionable inferences from large databases), and other areas (Bertini et al., 2006).

A knowledge base is a body of knowledge represented in a form that can be used by a program. An ontology is the set of objects, relations, concepts, and properties used by a particular domain of knowledge (Russell & Norvig, 2021). Knowledge bases need to represent things such as: objects, properties, categories and relations between objects, situations, events, states and time, causes and effects, knowledge about knowledge (what we know about what other people know); default reasoning (things that humans assume are true until they are told differently and will remain true even when other facts are changing); and many other aspects and domains of knowledge (Luger & Stubblefield, 2020). Among the most difficult problems in knowledge representation are: the breadth of common-sense knowledge (the set of atomic facts that the average person knows is enormous); and the sub-symbolic form of most commonsense knowledge (much of what people know is not represented as "facts" or "statements" that they could express verbally) (Kahneman, 2023). There is also the difficulty of knowledge acquisition, the problem of obtaining knowledge for AI applications.

Planning and Decision Making

An "agent" is anything that perceives and takes actions in the world. A rational agent has goals or preferences and takes actions to make them happen. In automated planning, the agent has a specific goal. In automated decision making, the agent has preferences, there are some situations it would prefer to be in, and some situations it is trying to avoid. The decision-making agent assigns a number to each situation (called the "utility") that measures how much the agent prefers it. For each possible action, it can calculate the "expected utility": the utility of all possible outcomes of the action, weighted by the probability that the outcome will occur. It can then choose the action with the maximum expected utility (Russell & Norvig, 2021).

In classical planning, the agent knows exactly what the effect of any action will be. In most real-world problems, however, the agent may not be certain about the situation they are in and it may not know for certain what will happen after each possible action. It must choose an action by making a probabilistic guess and then reassess the situation to see if the action worked (Russell & Norvig, 2021). In some problems, the agent's preferences may be uncertain, especially if there are other agents or humans involved. These can be learned (e.g., with inverse reinforcement learning) or the agent can seek information to improve its preferences. Information value theory can be used to weigh the value of exploratory or experimental actions. The space of possible future actions and situations is typically intractably large, so the agents must take actions and evaluate situations while being uncertain what the outcome will be.

A Markov decision process has a transition model that describes the probability that a particular action will change the state in a particular way, and a reward function that supplies the utility of each state and the cost of each action. A policy associates a decision with each possible state. The policy could be calculated (e.g., by iteration), be heuristic, or it can be learned. Game theory describes rational behavior of multiple interacting agents, and is used in AI programs that make decisions that involve other agents (Russell & Norvig, 2021).

Learning

Machine learning is the study of programs that can improve their performance on a given task automatically (Poole et al., 2020). Machine learning has been part of AI from the beginning. There are several kinds of machine learning. Unsupervised learning analyzes a stream of data and finds patterns and makes predictions without any other guidance. Supervised learning requires a human to label the input data first, and comes in two main varieties: classification (where the program must learn to predict what category the input belongs in) and regression (Russell & Norvig, 2021). In reinforcement learning the agent is rewarded for good responses and punished for bad ones. The agent learns to choose responses that are classified as good (Luger & Stubblefield, 2020). Transfer learning is when the knowledge gained from one problem is applied to a new problem. Deep learning is a type of machine learning that runs inputs through biologically inspired artificial neural networks for all of these types of learning.

Social Intelligence

Affective computing is an interdisciplinary umbrella that comprises systems that recognize, interpret, process or simulate human feeling, emotion and mood. For example, some virtual assistants are programmed to speak conversationally or even to banter humorously; it makes them appear more sensitive to the emotional dynamics of human interaction, or to otherwise facilitate human computer interaction. However, this tends to give naïve users an unrealistic conception of the intelligence of existing computer agents. Moderate successes related to affective computing include textual sentiment analysis and, more recently, multimodal sentiment analysis, wherein AI classifies the affects displayed by a videotaped subject (Poria et al., 2023).

Challenges of Artificial Intelligence (AI) Acceptability in Nigeria

Some of the challenges of accepting artificial intelligence applications in Nigeria as studied by Robinson (2018) include:

Complex Algorithms: Artificial intelligence is made up of huge amount of data and complicated algorithm which is a widely part of the technical side of artificial intelligence. Many researchers in Nigeria are utterly ignorant of these algorithms and technology, which makes it challenging for them to comprehend how AI works and as such avoidance of challenging task is rife.

Human-machine interface for artificial intelligence: The advanced skills needed to connect Nigeria with AI technology are in low supply and as such Nigerians are unable to get the most out of artificial intelligence; this result to a human skills gap in data science.

Reduced Investment: The unwillingness of some managers and business owners in Nigeria to invest in artificial intelligence is another issue with the technology. Not every business owner or firm in Nigeria can invest in artificial intelligence due to the high cost of setting it up and using it.

Software Failure: constant crash of hardware and software systems in Nigeria can be frustrating. Although no human technology is faultless, but in Nigeria, storage and retrieval mechanism is abysmal. As a result, human performed software tasks may be challenging to track. This kind of issue can be demoralizing and infuriating.

Religious and cultural barriers: the two biggest obstacles to progress in Nigeria are prejudice based on cultural identity and religion, thus AI technology is not exempt. Individuals with the same tribal affiliation tend to be biased in their cooperation with those from different tribes, particularly when it comes to knowledge acquisition. Similar to that, there is so much religious intolerance in Nigeria that it could substantially hinder AI development.

According to Sanni et al., (2022), challenges that face the Nigerian professional in the adoption of artificial intelligence application include:

Investment: artificial intelligence technology is very expensive; the cost for installation and maintenance is beyond the reach of the average businessman in Nigeria. The average business and the government is yet to fully incorporate AI into their value chain.

Software Malfunction: The automation system in which the artificial intelligence works on does not give space for an independent decision-making process. Instead, a decision-making power is controlled by machine and algorithms.

Lack of Political Will: The incessant change of government after successive election necessitates a state where implementation of artificial intelligence becomes near impossible. This is due in part to the change of government where the current government might abandon the project of the previous government or give it out to their stooge who might not be able to carry out the task. More so, electricity is needed for the full implementation of artificial intelligence, however, Nigeria is known to have an epileptic power supply. This is a major obstacle that must be overcome if artificial intelligence is to be adopted by professionals in Nigeria.

Limitations: AI, like any other technology, has limitations; it basically cannot carry out all tasks. However, it will result in the appearance of a new job sphere with multiple job profiles of varying quality.

Data Security: Due to the sensitivity of the massive classified data used by AI which oftentimes are personal and responsive, a lot of data theft, data breach as well as identity theft always occur in cyberspace. This is a big obstacle for business start-ups all over the world.

Software malfunction: Computer programmes are not free from errors. Software is bound to fail or malfunction. In most cases, it is difficult to locate the cause of the problem. With humans, tasks performed by people are constantly followed, but that of a programmes crash might be tedious to find out.

AI is not indispensable: AI is an instrument that strengthens and improves the implementation and productivity of humans. There is need to comprehend the fact that not all tasks can be handled by AI. It only has the control to operate all the common tasks with machines and allows you to do more useful errands alongside your time.

2.2 Empirical Review

Oladejo et al. (2018) explored the impact of AI on business performance within the Nigerian banking sector. Employing a quantitative research design with survey methodology and regression analysis, they evaluated the relationship between AI adoption—focusing on AI-driven customer service and fraud detection systems—and firm performance. Their findings revealed that AI positively influenced customer satisfaction and reduced operational costs by automating routine tasks, although challenges like inadequate infrastructure and the need for skilled AI management were noted. Chukwu et al. (2019) focused on AI applications in Nigeria's banking sector, particularly in fraud detection and financial transaction security. Using regression analysis, they assessed how AI reduced fraud-related losses and enhanced customer trust, which, in turn, improved firm performance by bolstering financial stability. Adebayo and Adesanya (2019) examined AI's role in decision-making processes within Nigerian manufacturing firms. Their study, based in Lagos, employed a mixed-methods approach combining qualitative interviews and quantitative analysis of firm performance data. They found that AI-based decision support systems improved operational efficiency and reduced production downtime, increasing profitability. However, they also highlighted gaps in employee readiness and the need for ongoing training to maximize AI benefits.

Nambudiri and Komala (2020) investigated AI's effects on firm performance within the telecommunications sector, using data from Nigerian subsidiaries of international telecom firms. The study employed Structural Equation Modeling (SEM) to assess AI's impact on service delivery, customer retention, and cost reduction. Results indicated that AI-powered CRM systems and chatbots enhanced customer interaction, lowered service costs, and improved customer loyalty, leading to better financial outcomes. Akintoye et al. (2020) studied the potential of AI in Nigeria's retail sector by examining AI-based recommendation systems and their effects on sales and customer engagement. Using a case study approach, they found that AI-driven personalized marketing strategies boosted consumer purchase behavior and increased store traffic, enhancing overall sales performance. AI adoption also allowed businesses to better understand customer preferences, leading to more tailored offerings. Ayodele et al. (2020) explored AI's role in improving credit risk management within Nigeria's financial sector. Through regression analysis, they demonstrated that AI algorithms analyzing customer data allowed financial institutions to make more accurate credit assessments, leading to reduced default rates and improved financial stability.

Ibraheem et al. (2021) assessed AI's influence on healthcare delivery in Nigerian public hospitals. Using a mixed-methods approach, including analysis of hospital management systems, clinical outcomes, and staff interviews, they found that AI applications in diagnostic imaging, patient scheduling, and treatment planning improved operational efficiencies, accelerated diagnoses, and enhanced treatment outcomes. Despite the positive impact, challenges such as data privacy concerns and staff resistance to AI adoption were identified. Ogunyemi and Akinbo (2021) examined the impact of AI-powered supply chain management systems on operational efficiency in Nigerian manufacturing firms. Their quantitative research, utilizing survey data and regression analysis, showed that AI tools such as predictive analytics and automated inventory management improved supply chain efficiency, reduced lead times, saved costs, and better aligned production schedules with market demand.

Ogbole et al. (2021) studied the impact of AI in energy management systems within Nigeria's energy sector. By combining quantitative analysis with case studies, they found that AI-based predictive maintenance and load forecasting systems improved the reliability and efficiency of energy supply, reducing downtime and operational costs. Yeboah et al. (2021) assessed AI's effect on firm performance in the retail sector across West Africa, particularly in Nigeria. Using a cross-sectional survey and structural equation modeling, they found that AI-based inventory management and demand forecasting led to improved stock management, reduced waste, and optimized pricing strategies. The research concluded that AI adoption positively affected financial performance and competitive positioning in Nigeria's retail sector. Zhang et al. (2017) investigated AI's impact on operational performance in China's manufacturing industry. Using structural equation modeling (SEM), they examined the effects of AI applications, such as robotics and predictive maintenance, on production processes. Results revealed that AI significantly reduced production costs, increased machine uptime, and improved product quality, leading to greater innovation and enhanced market share.

Müller et al. (2019) explored AI's impact on firm performance within Germany's automotive sector. By combining interviews with industry professionals and quantitative performance data, they found that AI applications like smart factories and autonomous vehicles improved production efficiency, reduced downtime, and enhanced customer satisfaction. AI also facilitated faster product development cycles and more personalized customer offerings, strengthening competitive advantage. Brynjolfsson and McAfee (2014) examined the broader implications of AI and automation across various industries in the United States. Their research focused on the relationship between AI-driven automation and productivity, arguing that AI could significantly enhance firm performance by increasing efficiency, improving decision-making, and optimizing resource allocation. They also discussed the challenges posed by workforce displacement and the need for upskilling to adapt to AI systems.

Sharma et al. (2020) conducted a study in India to explore AI's role in firm performance within the retail sector. Using quantitative research, they analyzed data from over 150 retail companies and found that AI-based tools for personalized recommendations, customer behavior analysis, and inventory management led to increased customer engagement, sales, and operational efficiency. The study also emphasized the importance of AI in enhancing customer loyalty and optimizing operational costs. Trivisonno et al. (2021) explored the role of AI-based decision support systems in Canada's healthcare sector. By combining quantitative analysis with case studies from Canadian hospitals, they found that AI systems improved diagnostic accuracy, reduced waiting times, and enhanced patient outcomes. Despite these benefits, the research pointed out challenges related to data security and AI integration with existing healthcare infrastructure.

Ritala et al. (2018) explored AI's role in fostering innovation within technology firms in Finland. Through qualitative interviews with executives and managers, they found that AI facilitated a culture of innovation by helping firms better understand market trends and customer preferences. Additionally, AI improved operational efficiency, sped up product development cycles, and enhanced service delivery, contributing to stronger competitive positioning.

Lima et al. (2020) examined AI's effect on supply chain management and firm performance in Brazil. Using a mixed-methods approach, they found that AI applications such as predictive analytics and route optimization significantly improved inventory management, reduced costs, and enhanced customer satisfaction. They also emphasized the critical role of data quality and infrastructure investment to fully realize the benefits of AI.

Lee et al.,(2020) explored AI's role in enhancing operational performance in Japan's manufacturing sector. They used a mixed-methods approach, including interviews with manufacturing managers and analysis of performance data from factories that implemented AI-driven predictive maintenance systems. The results showed that AI applications in predictive maintenance improved equipment uptime, reduced maintenance costs, and increased production efficiency. The study highlighted that companies with advanced AI capabilities outperformed those relying on traditional maintenance methods. Khan et al., (2020) investigated the role of AI in firm decision-making in Pakistan's service sector. Through a survey methodology, they collected data from over 150 firms, analyzing how AI-powered decision support systems influenced decision-making processes. The study found that AI systems enhanced decision-making speed and accuracy, leading to improved service delivery, cost reduction, and customer satisfaction. The research also identified challenges such as high implementation costs and resistance from employees concerned about job displacement.

Krause et al., (2018) explored AI adoption in the German automotive industry and its effects on firm performance. The study utilized a quantitative approach with data from over 100 automotive companies, applying Structural Equation Modeling (SEM) to examine the impact of AI on production processes and innovation. The study revealed that AI applications in autonomous vehicles and smart factories improved manufacturing efficiency and accelerated product development. Moreover, AI integration fostered innovation, which led to a more competitive position in the global market. Pereira et al. assessed the influence of AI on firm performance in Brazil's logistics sector. Using a case study approach, they explored how AI-powered route optimization and supply chain management systems impacted operational efficiency in logistics companies. Their findings indicated that AI led to significant reductions in fuel costs, improved delivery accuracy, and faster response times. However, they also noted that companies faced challenges in aligning AI tools with their existing logistics infrastructure.

Bauer and Riedl (2021) focused on the role of AI in enhancing customer service operations within Austrian banks. The study employed a survey methodology with regression analysis to evaluate how AI-powered chatbots and automated customer service systems influenced customer satisfaction and operational performance. The results demonstrated that AI significantly reduced customer wait times, improved service consistency, and increased overall satisfaction. However, some customers expressed concerns about AI replacing human customer service representatives.

Patel et al., (2021) examined the impact of AI adoption on human resource management in UK-based firms. Using a mixed-methods design, including interviews with HR managers and survey data, they assessed the role of AI in recruitment, employee performance management, and workforce planning. The study found that AI tools for candidate screening and performance evaluation improved recruitment efficiency and employee retention. However, it also pointed to challenges in addressing employee concerns about data privacy and algorithmic biases in AI decision-making.

2.3 Theoretical Framework

2.3.1 Resource Based View Theory

The Resource-Based View (RBV) of the firm, popularized by Barney (1991), provides a theoretical foundation for understanding how organizations achieve and sustain competitive advantage. Unlike external market-oriented perspectives, RBV emphasizes the importance of a firm's internal resources and capabilities in driving superior performance. According to the framework, resources must possess four characteristics: being valuable, rare, inimitable, and non-substitutable (VRIN), to provide long-term advantage. When firms succeed in acquiring, developing, and deploying such resources, they are better positioned to outperform competitors and achieve stronger financial outcomes. Resource based view theory offers a useful lens for explaining how AI adoption in accounting and financial reporting can enhance firm performance. AI systems, such as predictive analytics platforms, fraud detection mechanisms, and automated financial reporting tools, can be regarded as strategic resources. They are valuable because they improve efficiency, accuracy, and decision-making; rare, as not all firms possess the same infrastructure, expertise, or data required to implement AI effectively; inimitable, when developed on firm-specific datasets and embedded into unique workflows; and non-substitutable, when they become deeply integrated into the firm's processes and decision-making culture (Belhadi et al., 2021; Ghasemaghaei, 2021; Mikalef & Gupta, 2021).

Recent studies reinforce this theoretical perspective. Chen, Esperança, and Wang (2022) found that AI capabilities in e-commerce firms enhance creativity and decision-making, which in turn improve overall firm performance. Similarly, Cui (2025) demonstrated that AI-driven digital transformation in Chinese enterprises leads to better financial outcomes, especially when complemented by human AI collaboration and innovation practices. Further evidence suggests that firms that emphasize AI adoption achieve higher profitability, improved efficiency, and greater innovation efficiency compared to firms that rely solely on traditional resources (Resources Policy, 2023). AI has been conceptualized as a dynamic meta-capability that allows firms to orchestrate resources more effectively, adapt to environmental changes, and sustain long-term competitive advantage.

Anchoring this study on RBV is particularly valuable because it positions AI as more than just a technological tool. Instead, it is conceptualized as a strategic asset that contributes directly to firm financial performance when properly integrated with complementary resources such as skilled personnel, strong governance structures, and an innovation-driven organizational culture. This perspective also emphasizes that the mere acquisition of AI technologies does not automatically translate into performance gains; rather, firms must invest in developing capabilities that enable the effective use of AI in accounting and financial reporting. In doing so, AI becomes a core organizational competency that not only improves transparency and reduces inefficiencies but also provides the firm with a sustainable competitive edge.

2.3.2 Technology Acceptance Model

The first Technology Acceptance Model (TAM) was proposed by Davis et al. (1989) and has been widely employed by researchers to assess users' acceptability of information technologies (IT) (Usman et al., 2022; Qasim & Kharbat, 2020; Pedrosa et al., 2020; Varzaru, 2022). The model is characterized by two key constructs which are perceived ease of use and perceived usefulness which influence users' intention to adopt IT systems. Previous literature indicates that TAM is a well-recognized and widely acknowledged model for understanding the level of acceptance and adoption of digital technologies (Usman et al., 2022; Varzaru, 2022).

The constructs of perceived ease of use and perceived usefulness are especially relevant to artificial intelligent. Perceived usefulness reflects managers' and employees' expectations of how AI applications can enhance firm productivity, efficiency, and ultimately financial performance through cost reduction, improved decision-making, and revenue growth opportunities. Perceived ease of use, on the other hand, relates to the effort required for employees and decision-makers to integrate AI into business processes, which can determine the speed and extent of AI adoption within firms.

Despite its utility, TAM has limitations. It may overlook other important factors influencing AI adoption, such as organizational culture, leadership support, regulatory environment, or industry competitiveness (Muthia & Siti, 2023; Tulasi, 2022). TAM also assumes a static nature, implying that user perceptions remain consistent over time. However, in the case of AI, attitudes and beliefs may evolve as firms accumulate experience with the technology or as AI capabilities rapidly advance. Also, TAM's emphasis on behavioral intention rather than actual behavior limits its ability to fully capture how AI adoption translates into tangible improvements in firm financial performance (Bara'ah et al., 2022; Meiryani et al., 2021).

Moreover, AI adoption may not always follow purely rational decision-making patterns, as TAM suggests (Malatji et al., 2020). Firms may invest in AI not only for efficiency gains but also due to competitive pressure, regulatory compliance, or strategic positioning. According to Ferri et al. (2021b), perceived ease of use and perceived usefulness remain central motivational factors driving IT adoption. In AI's case, perceived usefulness may be linked to expectations of enhanced financial returns, while perceived ease of use reflects the organizational and employee effort involved in shifting to AI-enabled business models (Ferri et al., 2021a).

2.3.3 Agency Theory

Agency theory has its origins in economic theory, first introduced by Alchian and Demsetz (1972) and later developed by Jensen and Meckling (1976). The theory explains the contractual relationship between principals (owners and shareholders) and agents (directors, managers, and executives), in which decision-making power is delegated to the agent. However, agents may sometimes pursue objectives that are not aligned with those of the principals, thereby creating potential conflicts of interest. These conflicts often arise as a result of information asymmetry, where managers have access to more detailed knowledge about the firm's operations than shareholders (Ogoun, 2020).

The basic paradigm of agency theory was established in the economics literature of the 1960s and 1970s as an attempt to determine the optimal distribution of risk-sharing among individuals with divergent objectives (Jensen & Meckling, 1976). Over time, the scope of the theory expanded into the field of management, where it was applied to explain the need for cooperation between individuals with competing interests in order to achieve goal congruence within the firm (Kwafo, 2019). By the 1980s, agency theory had become increasingly relevant to accounting and auditing, particularly in the design of incentive contracts and the establishment of suitable monitoring mechanisms to align managerial behavior with shareholder interests (Gotthardt et al., 2020).

In its primitive form, agency theory describes a situation in which an agent is engaged by a principal to act on their behalf in return for compensation. Since both parties are assumed to be utility maximizers, motivated by both financial and non-financial incentives, conflicts are likely to emerge, particularly under conditions of uncertainty and information asymmetry

(Longinus, 2018). These conflicts create the need for control systems, such as financial reporting and auditing, which serve as mechanisms to reduce opportunistic behavior and build trust between principals and agents.

Agency theory is relevant to this study because its emphasis on the monitoring role of accounting and auditing. Artificial intelligence (AI), as a technological advancement in accounting practice, strengthens this monitoring function by reducing information asymmetry, enhancing the accuracy of financial reporting, and improving transparency. By automating routine tasks and detecting irregularities more effectively, AI helps to reduce agency costs, foster accountability, and align managerial decisions with shareholder interests. Ultimately, this contributes to improved financial reporting quality and stronger firm financial performance.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter contains the research procedures employed in this study which include; the research design, population of the study, the sample size and sampling techniques, operationalization variables, source of data, the research instrument, reliability and validity of the research instrument and the method of data analysis.

3.2 Research Design

The study basically adopted an exploratory research design in which structured questionnaire will be designed and distributed to the respondents as a means of gathering information. This design is most appropriate and suitable for measuring or ascertaining the impact of one variable on the other. The study employs research survey design since it seeks to ascertain respondents' current perception of the subject matter. As a result, the primary data for the study will be obtained by field survey of knowledgeable individuals with the administration of questionnaire to respondents

3.3 Population of the Study

The target population of this study are the employee of Banks within Ugbowo, Benin city, Edo State. This study population is limited to Ugbowo in other to facilitate easy collection of data due to the limited time available for this research.

3.4 Sample of the study

The study will randomly select 50 employees of the commercial banks within Ugbowo, Benin city. These randomly selected employees will serve as the sample of the study. The sample will focus on the employees in charge of customer care services and marketing/digital department of the banks because of the impact artificial intelligence usage plays in their duties.

3.5 Sources of Data

The source of data for this study is primary in nature. This source of information will be obtained through a questionnaire. The questions will be unambiguous and easy to answer.

3.6 Research Instrument

Data collection is very crucial in any research process. A questionnaire as a research instrument was mainly used for the collection of primary data. The questionnaire employs a typical form of fixed-response alternative questions that require the respondents to select from a predetermined set of answers to every question or fill in closed-ended statements. The questions were mainly sourced from a questionnaire of a related study. The questionnaire that will be administered to the respondents will be divided into two sections, of A and B. Section A is concerned with the demography data of the respondents among which are: age, gender, position held by respondent, years of experience. Section B consists of questions directly related to the objectives of the study and set in Likert scale.

3.7 Model Specification

This study examines the impact of artificial intelligence on firm financial performance. Given that the study will require a multiple regression analysis, a multiple regression model will also be derived. This multiple regression econometric model explains the variation in the value of the dependent variables which are based on a change in the independent variable captured by (chatbot application, robotic process automation, and AI application in decision making).

The model is described as follows:

The econometric model to be used in this study is adopted from the study of Kolapo et al., (2012) and Ogboi and Unaife (2012). Their original model is stated as follows:

ROA = f(CRM)…………………………………………………………….. (1)

Where: ROA = Return on Assets

CRM = Credit Risk Management

The original model was modified by including variables considered for this study.

Functionally, the model for the study is expressed as:

FFP = f(CA, RPA, AIPD) ………………………………………...…... (1)

This model is further expressed mathematically as:

$$FFP = = \beta_0 + \beta_1 CA_i + \beta_2 RPA_i + \beta_3 AIPD_i \ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

Where:

FFP = Firm Financial Performance

CA = Chatbot Application

RPA = Robotic Process Automation

AIAD = AI Application in Decision Making

i = respondents

μ = Error term

β_0 = Constant

β_{1-3} = Coefficients of the Independent variable

3.8 Operationalization of Variables

The study will examine the impact of the independent variable on the dependent variables. The focus of this study is to assess the impact of artificial intelligence on organization performance. The preliminary analysis of the data will be first conducted (descriptive statistics). For the purpose of this study firm financial performance serve as the dependent variable, while chatbot application, robotic process automation, and AI application in decision making remain the independent variable. This scale is constructed with close-ended questions, and they are organized as five-point Likert type (5=strongly agree, 4=agree, 3=neutral, 2=disagree, and 1=strongly disagree).

3.9 Method of Data Analysis

The ordinary least squares regression (OLS) was used in this study as a statistical method for analyzing the data gathered. This study adopts ordinary least squares regression because it estimates the relationships between one or more independent variables and a dependent variable. The EViews software was used to analyze the data. Preceding the analysis, the usual regression assumption tests were carried out. The serial correlation test was tested using the Breusch-Pagan test of serial correlation. Heteroskedasticity was tested using the Breusch-Pagan-Godfrey test while the model specification was carried out using the Ramsey RESET test.

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS AND INTERPRETATION

4.1 Introduction

In this chapter, the various variables employed in this study are tested, presented and interpreted in order to give meaningful results that can be used for decision purposes and policies. The chapter starts with descriptive statistics, followed by the Histogram Normality Test, Correlation analysis, and regression diagnostics which include: The Breusch-Pagan-

Godfrey Test of Heteroskedasticity, Breusch-Godfrey Test of Serial Correlation, Ramsey Reset Test and the regression analysis result.

4.2 Descriptive Statistics

The main features of a dataset are summarized by descriptive statistics. These statistics aid in comprehending the data's variability and central trend. The mean, median, and mode which stand for the average, middle value, and most frequent value, respectively are examples of measures of central tendency. Standard deviation, variance, minimum and maximum values, kurtosis, and skewness, on the other hand, are examples of variability measurements that show the distribution shape and dispersion of the data. The study variables' summary statistics are shown in the table below:

DESCRIPTIVE ANALYSIS

Table 1: Results of the Descriptive Analysis of the Regression Variables

	OP	CA	RPA	AIPD
Mean	6.5400	5.5000	5.2800	4.3200
Median	5.0000	5.0000	5.0000	4.0000
Maximum	17.000	12.000	8.0000	8.0000
Minimum	5.0000	5.0000	5.0000	3.0000
Std. Dev.	2.8227	1.2330	0.7570	0.8676
Skewness	2.2096	3.5298	2.6287	2.5559
Kurtosis	7.2056	17.208	8.6578	9.6752
Jarque-Bera	77.535	524.36	124.27	147.27

Probability	0.0000	0.0000	0.0000	0.0000
Sum	327.00	275.00	264.00	216.00
Sum Sq. Dev.	390.42	74.500	28.080	36.880
Observations	50	50	50	50

Source: Eviews 10

The data in table 4.1 above presents a statistical summary for four variables: Organization Performance (OP), Chatbot Application (CA), Robotic Process Automation (RPA), and AI Application in Decision Making (AIPD).

The central tendency measures observe that the average values for these variables are relatively close to each other. Organization Performance (OP) has the highest mean at 6.54, followed by Chatbot Application (CA) at 5.50, Robotic Process Automation (RPA) at 5.28, and AI application in decision making (AIPD) at 4.32. The median values show a slight difference from the means, suggesting that the distributions are not perfectly symmetric. While Op, CA and RPA have a median of 5.00, AIPD has a lower median of 4.00.

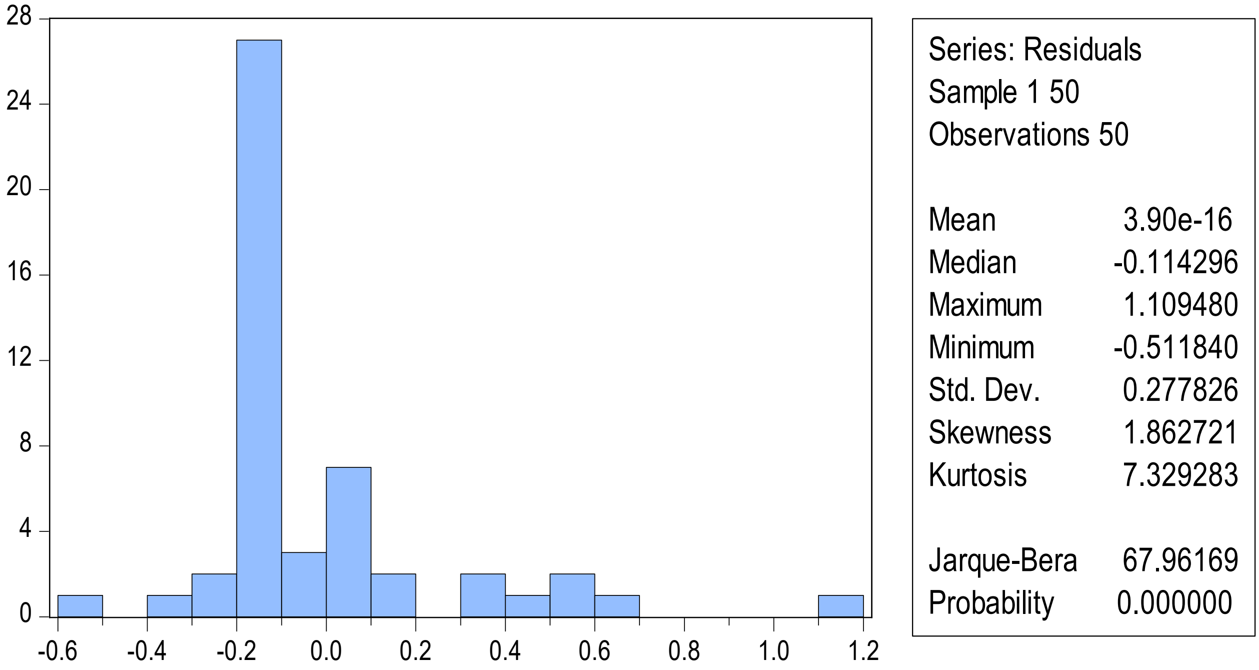
In terms of variability, the standard deviations indicate a moderate spread of the data for all variables, with organization performance (OP) showing the most dispersion (2.82), followed closely by chatbot application (CA) and AI application in decision making (AIPD) with standard deviations of 1.23 and 0.86, respectively. Robotic process automation has the least variation, with a standard deviation of 0.76.

The skewness values for all four variables are positive, suggesting that their distributions are slightly skewed to the right. The skewness of CA is the highest (3.53), indicating the most pronounced positive skew, while OP has the least skew (2.21), pointing to a nearly symmetric distribution.

The results from the Jarque-Bera test provide insight into the normality of these distributions. Organization performance, chatbot application, robostic process automation and AI application in decision making have a Jarque-Bera statistic of 77.53, 524.36, 124.27, and

147.27 respectively, with all having a probability of 0.0000, suggests that all variables considered are not normally distributed. The mean skewness, kurtosis and Jarque-Bera statistics are reported in the result of the histogram normality test in Fig 1.

Fig 1: Result of the Histogram Normality Test



The results of the histogram normality test show a positive skewness value of 1.862721, indicating a right-skewed distribution. The kurtosis value of 7.329283 is slightly higher than the benchmark of three, suggesting a leptokurtic distribution with a sharper peak. The degree of variability around the mean is indicated by the mean standard deviation, which is 0.277826. Furthermore, given the high significance of the test results, the Jarque-Bera statistic of 67.96169 with a probability value of 0.000000 indicates that the data do not fit a Gaussian normal distribution.

4.3 Correlation Analysis

Table 2: Result of the Correlation Analysis

Covariance Analysis: Ordinary
Date: 28/09/25 Time: 12:29
Sample: 1 50
Included observations: 50

Correlation t-Statistic Probability	OP	CA	RPA	AIPD
OP	1.0000 ----- -----			
CA	0.5110 4.1186 0.0001	1.0000 ----- -----		
RPA	0.1310 0.9156 0.3644	0.0707 0.4909 0.6257	1.0000 ----- -----	
AIPD	0.3397 2.5021 0.0158	0.4090 3.1049 0.0032	0.2632 1.8901 0.0648	1.0000 ----- -----

Source: Eviews 10

The analysis reveals the relationships between the four variables: Organization Performance (OP), Chatbot Application (CA), Robotic Process Automation (RPA), and AI Application in Decision Making (AIPD). Firstly, there is a moderate positive relationship between Organization performance and chatbot application. As one of these variables increases, the other tends to increase as well, though the relationship is not extremely strong. Similarly, OP and both robotic process automation and AI application in decision making exhibit positive correlations. In each case, an increase in robotic process automation and AI application in decision making is associated with increases in organization performance, suggesting that higher robotic process automation and AI application in decision making may be linked to better conditions for organization performance.

A weak positive relationship is observed between robotic process automation and chatbot application in business. Their relationship means that an increases in one is associated with increases in the other. This suggests that entities with higher robotic process automation may benefit more from the use of chatbot application. In addition, Ai application in decision making and chatbot application share a weaker but still positive relationship, indicating that as Ai application in decision making increases, so does the likelihood of chatbot application.

Finally, Ai application in decision making and robotic process application have a relatively weak positive relationship, suggesting that businesses benefiting from Ai application in decision making are also likely to experience more favorable conditions for robotic process application.

4.4 Regression Diagnostics

Test of Heteroskedasticity

Table 3: Test of Heteroskedasticity

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.078059	Prob. F(3,46)	0.9716
Obs*R-squared	0.253250	Prob. Chi-Square(3)	0.9686
Scaled explained SS	0.678344	Prob. Chi-Square(3)	0.8783

Source: Eviews 10

Table 3 displays the results of the Breusch-Pagan-Godfrey test for heteroskedasticity. The probability value obtained is 0.9716, which is greater than 0.05. This suggests that there is no issue of heteroskedasticity in the model. Therefore, the alternative hypothesis of homoskedastic residuals is accepted, indicating that the variance of the residuals in the regression model is constant.

Test of Serial Correlation

Table 4: Result of the Breusch-Godfrey Test of Serial Correlation

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.695341	Prob. F(2,44)	0.0787
Obs*R-squared	5.457185	Prob. Chi-Square(2)	0.0653

Source: Eviews 10

The results from the Breusch-Godfrey Serial Correlation LM Test suggest that there is no significant issue with serial correlation in the model. The F-statistic is 2.695341, and its associated probability value (Prob. F(2,44)) is 0.0787, which is highly insignificant. This indicates that the null hypothesis of no serial correlation is accepted, suggesting that there is no serial correlation present in the residuals of the regression model.

Ramsey Reset Test

Table 5: Results of the Ramsey Reset of Model Specification

Ramsey RESET Test
Equation: UNTITLED
Specification: OP CA RPA AIPD C
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	0.350243	45	0.7278
F-statistic	0.122670	(1, 45)	0.7278
Likelihood ratio	0.136115	1	0.7122

Source: Eviews 10

The probability value of 0.7278, which is higher than 0.05, as indicated by the Ramsey RESET model specification test findings. This result implies that a regression model with a misspecified null hypothesis cannot be maintained. As a result, the study's alternate hypothesis of a well-defined model is approved.

4.5 Analysis of the Regression Result

Table 6: Result of the Regression Analysis

Dependent Variable: OP
Method: Least Squares
Date: 28/09/25 Time: 12:26
Sample: 1 50
Included observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CA	0.852667	0.259294	3.288418	0.0019
RPA	0.167219	0.345624	0.483817	0.6308
AIPD	0.272886	0.276832	0.985743	0.3294
C	-0.296009	0.664740	-0.445300	0.6582

R-squared	0.285261	Mean dependent var	1.814727
Adjusted R-squared	0.238648	S.D. dependent var	0.328624
S.E. of regression	0.286743	Akaike info criterion	0.416155
Sum squared resid	3.782181	Schwarz criterion	0.569117
Log likelihood	-6.403874	Hannan-Quinn criter.	0.474404
F-statistic	6.119726	Durbin-Watson stat	1.345240
Prob(F-statistic)	0.001363		

Source: Eviews 10

Table 6 above displays the regression analysis's outcome. According to the preliminary analysis, the independent variables taken into consideration in this study are chatbot application, robotic process application and AI application to decision making, and they contribute to 28.52% of the variation in organization performance, with a coefficient of multiple determination of 0.285261 and an adjusted value of 0.238648. The error term, however, captures the remaining 71.48%. The combined statistical significance of all the explanatory factors is indicated by the F statistics value of 6.119726 which is more than 2.

4.6 Test of Hypotheses

Hypothesis One: Chatbot application in business has no significant impact on organization performance.

The coefficient for chatbot application (CA) is 0.852667, which suggests a positive relationship between chatbot application in business and organization performance. This means that, holding other variables constant, an increase in the use of chatbot application in business is associated with an increase in organization performance. The t-statistic for chatbot application is 3.288418, and the corresponding probability of 0.0019 indicates that the effect of chatbot application in business on organization performance is statistically significant at the 5% level. Therefore, the null hypothesis of chatbot application in business having no significant effect on organization performance in Nigeria is rejected at 5% level of significance.

Hypothesis Two: Robotic process automation has no significant effect on organization performance.

The coefficient for robotic process automation (RPA) is 0.167219, suggesting a very weak positive relationship between robotic process automation and organization performance. However, the t-statistic is 483817, and the probability is 0.6308, which is much higher than the typical 0.05 threshold for statistical significance. This means that the effect of robotic process automation on organization performance is not statistically significant, implying that robotic process automation does not have a meaningful impact on organization performance in this model. Therefore, the null hypothesis is accepted at 5% level of significance.

Hypothesis Three: Artificial Intelligence application in decision making has no significant impact on organization performance.

The coefficient for artificial intelligence applications in decision making (AIPD) is 0.0.272886, indicating a positive relationship between artificial intelligence applications in decision making and organization performance. This suggests that an increase in artificial intelligence applications in decision making is associated with an increase in organization performance, holding other variables constant. The t-statistic for artificial intelligence applications in decision making is 0.9857, and the probability of 0.3294 shows that this relationship is statistically insignificant at the 5% level, suggesting that artificial intelligence applications in decision making has no significant impact on organization performance. Therefore, the null hypothesis of artificial intelligence applications in decision-making having no significant effect on organization performance is accepted at 5% level of significance.

4.7 Discussion of Findings

The first hypothesis stated that chatbot applications would have no significant impact on organizational performance. The results, however, indicate a positive and statistically significant relationship between chatbot applications and organizational performance, with a coefficient of 0.852667. This finding suggests that an increase in chatbot adoption leads to improved performance within businesses. The t-statistic of 3.288418 and the corresponding p-value of 0.0019 confirm the statistical significance of the relationship at the 5% significance level, leading to the rejection of the null hypothesis. This positive effect aligns with findings from previous research that emphasize the value of chatbots in improving customer service and operational efficiency. A study by Gnewuch et al. (2017) found that chatbots enhance customer engagement and streamline business processes, which in turn boosts organizational performance.

The second hypothesis, which suggested that RPA has no significant effect on organizational performance, was supported by the findings. The coefficient for RPA was 0.167219, showing a weak positive relationship with organizational performance, but the t-statistic of 0.483817 and the high p-value of 0.6308 indicate that this relationship is not statistically significant at the 5% level. This implies that RPA does not have a meaningful impact on organizational performance, and the null hypothesis is accepted. This outcome contrasts with earlier studies that demonstrate the potential of RPA to improve organizational efficiency and performance. According to Westerman et al. (2014), RPA can automate routine, time-consuming tasks, allowing employees to focus on more strategic activities, thereby enhancing organizational outcomes.

The third hypothesis examined the effect of AI applications in decision-making on organizational performance. The results indicated a positive but statistically insignificant relationship, with a coefficient of 0.272886 and a t-statistic of 0.9857. The p-value of 0.3294 suggests that AI applications in decision-making do not significantly impact organizational performance in the Nigerian context. As a result, the null hypothesis is accepted, meaning that AI applications in decision-making have no significant effect on organizational performance at the 5% level. This finding is consistent with the mixed results observed in previous literature. While AI applications in decision-making are widely recognized for their potential to improve business strategies and performance (Brynjolfsson & McAfee, 2014), the impact on organizational performance may be contingent on factors such as the quality of data, organizational readiness, and the specific decision-making processes being supported by AI. A study by Dastin (2017) found that AI applications in decision-making can be powerful, but only when businesses have robust systems in place to leverage the technology effectively. The lack of significance in this study might suggest that AI decision-making tools are still underutilized or not fully integrated into organizational processes in Nigeria.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS

The findings from the analysis of the data on the impact of artificial intelligence of organization performance are summarized in this section from which conclusions are drawn and recommendations are made.

5.1 Summary of Findings

1. Chatbot Application (CA) has a positive and statistically significant relationship with Organization Performance (OP), indicating that as the use of chatbot applications in business increases organizational performance improves.
2. Robotic Process Automation (RPA) shows a very weak positive relationship with Organization Performance (OP), but this relationship is not statistically significant.
3. Artificial Intelligence Applications in Decision Making (AIPD) has a positive relationship with Organization Performance (OP), with a coefficient of 0.272886. However, the t-statistic of 0.9857 and the probability of 0.3294 suggest that the effect of artificial intelligence applications in decision making on organizational performance is statistically insignificant at the 5% level.

5.2 Conclusion

The study examines the impact of artificial intelligence applications on organization performance. The study data was gathered from a well-structured questionnaire filled by 50 employee on Nigeria banks with Ugbowo, Benin city, Edo State. The employee in charge of customer care services and marketing/ digital marketing of the banks are mostly considered in the study. Different statistical and econometric measures were carried out and the empirical results revealed both a positive and negative relationship between the variables considered. Conclusively, the findings indicated that Chatbot application have a positive and statistically significant impact of organization performance. Robotic process automation and AI application in decision making have a positive but statistically insignificant impact on organization performance.

5.3 Recommendations

Based on the findings from the regression analysis, the following recommendations are made:

1. Businesses should consider increasing their investment in chatbot technologies, since chatbot applications have a positive and statistically significant impact on organizational performance. Chatbots can improve customer service, streamline operations, and enhance overall efficiency, contributing to better organizational outcomes.
2. Organizations should reassess the effectiveness of their RPA strategies, possibly focusing on other automation tools or refining current RPA systems to ensure they add value to operations.
3. Business should explore other AI areas like predictive analytics, customer insights, or process automation. It may be beneficial to focus on AI applications that can deliver more immediate, tangible results in organizational performance.
4. Based on the results, prioritizing technologies and tools that have shown statistically significant improvements, such as chatbots, should be a key focus. This approach ensures that resources are being allocated to initiatives that can meaningfully impact organizational success.
5. Business should explore deploying chatbots in various functions beyond customer service. For instance, chatbots can be used in HR for employee inquiries, in finance for transaction assistance, or in sales for lead generation.

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APPENDIX I

QUESTIONNAIRE

Department of Accounting,

University of Benin,

Benin city, Edo State.

Dear Respondent,

I am inviting you to participate in this academic research by completing this questionnaire. The objective of this research is to explore the impact of artificial intelligence on organization performance. The questions contained herein will only require approximately 5 – 6 minutes of your time to complete. I express my profound gratitude for your contribution and assistance in completing this research. You are not in any way obligated to answer these questions, but your responses will help my research significantly. Please be rest assured that the information you provide here will be handled with utmost confidentiality and will be used solely for the purpose stated above.

Yours sincerely

Dowell Gift Oyinpresidor

SECTION A: Demographic Information

Instruction: Please tick the respective boxes to indicate your response.

Demographic Variables	**Responses**
Gender	Male { } Female { }
Age	25-30 years { } 31 -40 years { } 41- 60 years { }
Religion	Christianity { } Islam { } Other (Please Specify) ___________
Years of experience	1-10 years { } 11-20 years { } 21 years and above { }

Section B: Instruction

Scaling from 1–5 for decisions of respondents has been provided below, kindly indicate your degree of agreement to the statement by filling the spaces provided with a tick (✓). Note: Strongly Disagree (SD); Disagree (D); Neutral (N); Agree (A); Strongly Agree (SA)

Research Questions on Organization Performance

S/No	Statements	SA	A	N	D	SD
1.	Organization consistently meets its performance targets.					
2.	Organization has clear performance standards and goals.					
3.	AI helps the organization reduce operational costs					
4.	AI leads to better resource management and allocation within the organization.					
5.	AI implementation makes it easier to identify and address performance gaps within the organization.					

Research Question 1: Chatbot application and organization performance

S/No	Statements	SA	A	N	D	SD
6.	The integration of chatbot applications in business improves overall organizational performance.					
7.	Chatbots application in business enhances customer service efficiency in the organization.					
8.	Chatbots lead to cost reductions by automating repetitive tasks in the organization.					
9.	Chatbots improve the accuracy of information provided to customers.					
10.	Employees find the chatbot application helpful in streamlining their daily tasks.					

Research Question 2: Robotic process automation and organization performance.

S/N	Statements	SA	A	N	D	SD
11.	The implementation of robotic process automation (RPA) significantly improves overall organizational performance.					
12.	Robotic process automation improves the accuracy and quality of work within the organization.					
13.	The use of robotic process automation enhances the speed of decision-making processes within the organization.					
14.	The use of robotic process automation reduces human errors in repetitive tasks.					
15.	Robotic process automation contributes to the organization’s ability to meet its performance targets.					

Research Question 3: AI application in decision-making and Organization performance.

S/No	Statements	SA	A	N	D	SD
16.	The use of AI applications improves decision-making within the organization.					
17.	AI tools enhance the speed of decision-making in the organization.					
18.	AI applications improve the accuracy of decisions made within the organization.					

19.	The organization experiences increase productivity due to AI-driven decision-making.					
20.	The use of AI in decision-making reduces human biases in the organization's decision processes.					

APPENDIX II

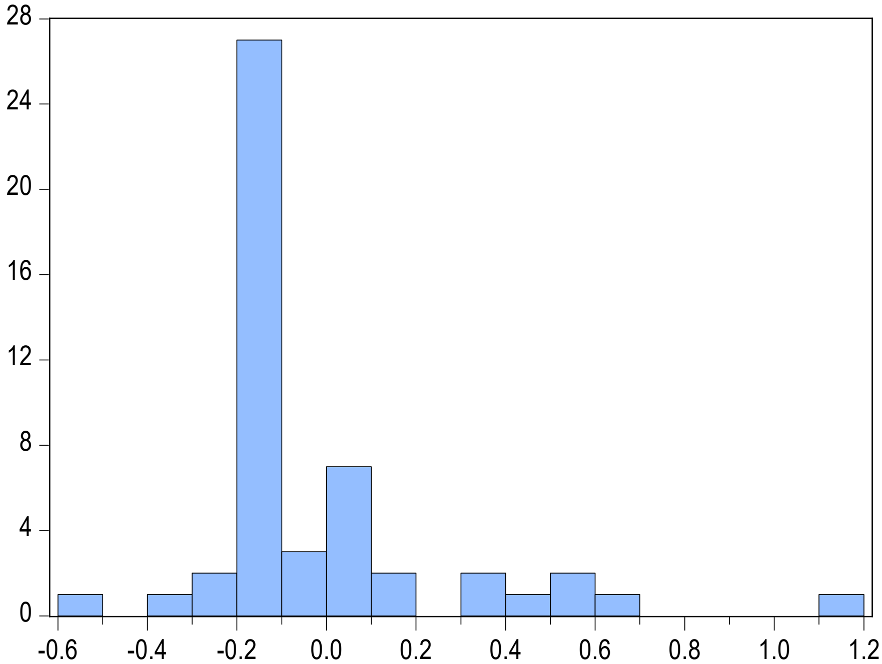
Descriptive Analysis Result

	OP	CA	RPA	AIPD
Mean	6.5400	5.5000	5.2800	4.3200
Median	5.0000	5.0000	5.0000	4.0000
Maximum	17.000	12.000	8.0000	8.0000
Minimum	5.0000	5.0000	5.0000	3.0000
Std. Dev.	2.8227	1.2330	0.7570	0.8676

Skewness	2.2096	3.5298	2.6287	2.5559
Kurtosis	7.2056	17.208	8.6578	9.6752
Jarque-Bera	77.535	524.36	124.27	147.27
Probability	0.0000	0.0000	0.0000	0.0000
Sum	327.00	275.00	264.00	216.00
Sum Sq. Dev.	390.42	74.500	28.080	36.880
Observations	50	50	50	50

APPENDIX III

Histogram Normality Test



Series: Residuals
Sample 1 50
Observations 50

Mean	3.90e-16
Median	-0.114296
Maximum	1.109480
Minimum	-0.511840
Std. Dev.	0.277826
Skewness	1.862721
Kurtosis	7.329283
Jarque-Bera	67.96169
Probability	0.000000

APPENDIX IV

Correlation Analysis Result

Covariance Analysis: Ordinary
Date: 28/09/25   Time: 12:29
Sample: 1 50
Included observations: 50

Correlation t-Statistic Probability	OP	CA	RPA	AIPD
OP	1.0000 ----- -----			
CA	0.5110 4.1186 0.0001	1.0000 ----- -----		
RPA	0.1310 0.9156 0.3644	0.0707 0.4909 0.6257	1.0000 ----- -----	
AIPD	0.3397 2.5021 0.0158	0.4090 3.1049 0.0032	0.2632 1.8901 0.0648	1.0000 ----- -----

APPENDIX V

Regression Analysis Result

Dependent Variable: OP
Method: Least Squares
Date: 28/09/25 Time: 12:26
Sample: 1 50
Included observations: 50

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CA	0.852667	0.259294	3.288418	0.0019
RPA	0.167219	0.345624	0.483817	0.6308
AIPD	0.272886	0.276832	0.985743	0.3294
C	-0.296009	0.664740	-0.445300	0.6582

R-squared	0.285261	Mean dependent var	1.814727
Adjusted R-squared	0.238648	S.D. dependent var	0.328624
S.E. of regression	0.286743	Akaike info criterion	0.416155
Sum squared resid	3.782181	Schwarz criterion	0.569117
Log likelihood	-6.403874	Hannan-Quinn criter.	0.474404
F-statistic	6.119726	Durbin-Watson stat	1.345240
Prob(F-statistic)	0.001363		