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The role of artificial intelligence and financial engineering for listed service companies in Nigeria

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ABSTRACT

This study examines the role of artificial intelligence (AI) in the financial engineering of listed service companies in Nigeria. The study used a survey field alongside secondary data from the financial statements of the service companies listed in the Nigerian Exchange Group. Self-structured questionnaires were administered through online platforms. The respondents were drawn from the staff of the service companies having access to AI and among the strata of practicing auditors and accountants with a clear understanding and good knowledge of AI applications and capabilities in solving financial engineering-related issues. The study utilized 487 validated responses in total. The Cronbach Alpha test was performed to confirm the validity and reliability of the instrument. Using the Statistical Program for the Social Sciences (SPSS) program, descriptive and inferential statistics were used to evaluate the obtained data. The results demonstrated that AI had a significant effect on product engineering and process engineering. Also, AI had a significant effect on financial solution engineering and, lastly, on human efficiency and productivity engineering in listed service companies in Nigeria. Managers can use the research findings to brace AI in business transactions to provide creative financial solutions, increased productivity, and increased competitiveness in the sector of digital service delivery.

Contribution/Originality: This study is the first to examine the effect of artificial intelligence on the financial engineering of listed service companies in Nigeria. The study demonstrates that firms using AI automate more complex processes and save downtime. It establishes that AI enhances better employee predictive abilities to enhance the quality, efficiency, and creativity of employee decisions.

1. INTRODUCTION

Analysts have created a phrase known as financial engineering to describe the process of evaluating and enhancing a variety of financial decision-making processes, including risk management, financial portfolio planning, forecasting, trading, hedging, fraud detection, and other applications. Financing engineering has effectively integrated a number of quantitative analytic fields, including statistics, data mining, artificial intelligence, time series, probability, and mathematics. In digital corporate operations, financial engineering is a cross-disciplinary field. At its core, financial engineering approaches the study of finance from an engineering methodology and perspective. The scope of study and application is wide and diverse. It includes and uses information from a variety of subjects, including financial theory, computer science, economics, and mathematics. Financial theory translation into real-world financial sector applications is a major component of financial engineering. A vast and multifaceted topic of study and practice, "financial engineering" integrates engineering concepts with the finance industry (Ashta & Herrmann, 2021; Chen, Sangaiah, Chen, Lughofer, & Egrioglu, 2022).

Financial engineering is the use of analytical models for the resolution of financial issues. The disciplines of economics, statistics, applied mathematics, and computer science are all used in this process. These technologies aid in creating new financial products and in resolving current financial problems. Quantitative analysis is another name for financial engineering. In essence, it is a plan for business reorganization. Commercial banks, insurance companies, and investment banks all use this method. Financial engineering is utilized in the financial industry for a variety of activities (Omoge, Gala, & Horky, 2022). Corporate finance, arbitrage trading, computer technology and automated finance, risk analyses and management, option and other financial derivatives pricing, behavioural finance, the creation of unique financial instruments and structured financial products, quantitative portfolio management, credit management, and credit risk are some of the areas where it is most frequently used.

To solve issues, financial analysts develop, construct, and put into practice innovative financial models and procedures (Ngure, Kimani, & Kariuki, 2017). Financial experts are always looking for new business ventures. Such models need extensive study to develop and rely on stochastics, risk analysis, simulations, and in-depth data analysis. Financial engineers are knowledgeable in corporate finance, economics, and statistics. These experts work in financial management, consulting firms, securities, and banking. Financial engineering is used in the financial services industry in a wide variety of ways, including corporate finance, risk management, and the creation of financial derivative products. Others, however, contend that excessive reliance on financial engineering without taking into account the difficulties involved leads to financial problems and severe financial disasters, such as the Global Financial Crisis of 2008. Although widely accepted and used, the discipline of financial engineering is not without criticism. Academics in the fields of economics, mathematics, and even financial engineering itself have harshly criticized some applications of the subject (Hussain, Rehman, & Işık, 2022; Rabbani, Sarea, Khan, & Abdullah, 2022).

Incidentally, financial engineering is burdened with a myriad of challenges impeding its flexibility and effectiveness in solving targeted problems. The problem of financial engineering and other associated challenges can be better handled with the application of digital solutions like artificial intelligence. Financial engineering is laden with problems associated with environmental factors, which are those that are present in the surrounding environment and directly affect the company (Hamadneh et al., 2021; Hentzen, Hoffmann, Dolan, & Pala, 2022).

In addition, certain elements beyond our control affect financial engineering. We opined that financial engineering suffers from political, economic, social, and technological (PEST) factors that have huge impact on sustainable financial engineering. Technological advances, new discoveries, competition, and political and economic changes are frequent environmental variables. The internal company variables have a direct impact on the financial engineering process. Accounting procedures, risk aversion, agency conflicts, and liquidity demands are a few examples of intra-firm issues. In resolving the problem of financial engineering, artificial intelligence has been considered in the literature. Karim, Rabbani, and Bawazir (2022) reported that artificial intelligence had a significant effect on financial engineering. Iman, Sharul, and Azam (2019) posited that there had been a close connection between artificial intelligence in resolving corporate products and service re-engineering in creating value for stakeholders.

The ability of a computer-controlled robot or digital system to accomplish tasks often performed by intelligent humans is known as artificial intelligence (AI) (Holzinger, Langs, Denk, Zatloukal, & Müller, 2019; Karim et al., 2022). The phrase is commonly used to refer to the efforts being made to create artificial intelligence systems with cognitive abilities comparable to those of humans, including the capacity for reasoning, meaning-making, generalization, and experience-based learning. Artificial intelligence can be defined as the methodical analysis of a large number of options to arrive at a preset outcome or answer. There are two types of problem-solving techniques: specialized and universal. A special-purpose approach is created specifically to deal with a specific problem and often leverages highly specific aspects of the context in which the problem is embedded.

The next big thing in customer service is artificial intelligence (AI), which has the potential to address a common issue for businesses: the overwhelming amount of data (Ionescu, 2019). The customer service industry is being revolutionized by augmented intelligence technology, which will make it more effective, efficient, and profitable. According to Khalifaturofi'ah (2021), most firms find it challenging to respond to customer inquiries. For example, they may need to hire more staff members to keep up with the increase in customer traffic. The simultaneous effective and efficient handling of all customer requests is required. According to Kiprotich and Onsomu (2021), and Ibraheem (2013), businesses with a large volume of one-off customers would prefer to wait five minutes on hold with a live person rather than twenty for an automated callback.

The problem of this study resides with financial engineering and its implications for solving corporate-related challenges. However, the application of artificial intelligence is one of the most demanding, and fast-paced sectors now heavily depend on artificial intelligence. AI-based automation can assist in easing the load of financial transaction processing, audits, and compliance requirements towards enhancing financial engineering for interested organizations (Haenlein & Kaplan, 2019).

In the industrial sector, artificial intelligence (AI) and machine learning (ML) have significantly increased output, leading to a number of amazing successes. In our fast-paced digital era, a number of industries are successfully using AI to increase business expansion, profitability, and sustainability (Hamadneh et al., 2021). Among these is the banking sector, which is well-known and has a lot of promise for artificial intelligence. Consumers' desire for financial independence and capacity to manage their financial well-being are what are driving the use of AI in personal finance. Artificial intelligence (AI) is necessary for any financial institution looking to dominate the market, whether it's producing insights for wealth management products or providing chatbots with 24/7 financial assistance.

Listed service companies in Nigeria stand to gain a great deal from the application of AI since it can more accurately identify and assess credit risks. Machine learning and other AI technologies may enhance loan underwriting and lower financial risk for businesses trying to add value. By enhancing fraud detection and exposing fraud, artificial intelligence (AI) could help reduce financial crime anomalous behavior, while corporate accountants, analysts, treasurers, and investors work to promote long-term growth (Al-Araji, Al-Din, & Mayada, 2020). The manner and procedures by which companies in Nigeria and individuals manage their finances are changing as a result of artificial intelligence (AI). In fact, out of all firms and businesses, banks have taken note of the developing advantages of AI in finance, with 80% of them realizing the good it can bring (Faccia, Al Naqbi, & Lootah, 2019; Gunning & Aha, 2019). However, banks, as one of the service companies, may save billions of dollars only by eliminating unnecessary financial activities. Arli, Esch, Bakpayev, and Laurence (2021) opined that according to research by EY, 65% of finance directors want to give automating and standardizing operations top priority in order to increase organizational agility. This is especially important for finance teams that want to eliminate tedious duties so they can devote more time to important projects that benefit their companies.

The comfort and needs of the customer are at the center of today's banking services, which also make effective use of artificial intelligence and creative financial service processes (Acemoglu & Restrepo, 2018). The banking sector's usage of AI in its financial system has enhanced the flow of financial data and made a wider clientele available. Artificial intelligence has continued to be a source of inspiration for or exploration by science fiction authors. However, there has been a discernible rise in recent years. AI has begun to be used in practical applications, notably in corporate settings. There are three causes of it: Data is accessible: Both organized (in databases) and unstructured (in files, photos, and videos) data are being produced at an astounding rate in our digital environment. The more data that is provided as input, the more accurate the forecast output is; data is the "new oil" that clever algorithms consume. The ability to evaluate the data at a fair cost and in an acceptable length of time is now possible because of the flexibility and possibility created in the application of artificial intelligence (Al-Sayyed, Al-Aroud, & Zayed, 2021; Gunning & Aha, 2019).

The primary objective was to investigate how artificial intelligence directly affects the financial engineering of listed service organizations in Nigeria. In consideration of data mining services, credit evaluation and scoring applications, trading algorithms, robotics and machine learning, and employees' emotional intelligence and knowledge in impacting financial engineering from the perspectives of product engineering, process engineering, and financial solution engineering, researchers' interest is to provide a deeper significance of artificial intelligence on the innovative desirability of Nigerian service-listed companies. We acknowledge that the field of artificial intelligence (AI) is broad and difficult to classify. Here, we concentrate on the rational agent approach to AI, which describes computer systems that work to attain the best possible result in light of predetermined goals.

This study is motivated by several limitations of the existing literature in considering the nexus between artificial intelligence and financial engineering, and evidently, the dearth of literature in Nigeria that has researched the effect of artificial intelligence on financial engineering. Some prior studies have extensively considered artificial intelligence from the perspective of advanced economies (Hentzen et al., 2022; Hussain et al., 2022). But the case of artificial intelligence from the point of view of financial engineering as an emerging technological innovation has not been given adequate attention, as it has remained under-researched, creating a wide empirical landscape for research studies in the Nigerian literature. In this study, we bridged the gap and contributed to the knowledge as we explored the implications and effects of artificial intelligence in solving the problem of financial engineering in the listed service companies in Nigeria. This would provide an improvement and offer empirical evidence and usefulness in making managerial and investment decisions capable of adding economic value to companies by meeting set goals.

In addressing the problem of financial engineering, there is a need to bring new ideas using artificial intelligence to Nigerian service companies. Consequently, it examined the effect of artificial intelligence on the financial engineering for listed service companies in Nigeria. In this regard, the study posited the following research hypotheses:

Research Hypothesis (Ho_1): There is no significant effect of artificial intelligence on the product engineering for listed service companies in Nigeria.

Research Hypothesis (Ho_2): Artificial intelligence does not significantly affect the process engineering for listed service companies in Nigeria.

Research Hypothesis (Ho_3): There is no significant effect of artificial intelligence on the financial solution engineering for listed companies in Nigeria.

Research Hypothesis (Ho_4): Artificial intelligence has no significant effect on human resource efficiency and production engineering for listed service companies in Nigeria.

The remainder of the investigation was seen in the following light: The study provided a review of the literature and a theoretical framework in Section 2. The study's methodology was discussed in Section 3. The data analysis, findings, interpretation of findings, and discussion were presented in Section 4. Section 5 of the study provided a conclusion, recommendations, and ideas for additional research.

2. LITERATURE REVIEW/THEORETICAL FRAMEWORK

2.1. Financial Engineering

The use of analytical models for financial issues is known as financial engineering. Financial engineering solves contemporary financial issues and develops original and creative financial solutions by utilizing techniques and information from the domains of artificial intelligence, statistics, economics, and applied mathematics. Conventional commercial banks, investment banks, insurance companies, and hedge funds all use financial engineering, also known as quantitative analysis. Financial engineers use quantitative risk models to assess the risks associated with each product offering in light of market volatility as well as whether a new financial product would be feasible and profitable in the long run. Financial engineers collaborate with hedge funds, asset management organizations, insurance companies, and other service providers operating in Nigeria.

In the interdisciplinary discipline of financial engineering, programming techniques, engineering techniques, mathematical tools, and financial theory are all used. It has also been described as using technical approaches, particularly those from computational and mathematical finance, in the practice of finance (Kiprotich & Onsomu, 2021). Applications of numerical methods, computer science, statistics, and economic theory are used in financial engineering. Someone who employs technical instruments in finance, such as a software engineer in a bank or a researcher in a public finance department, might be referred to as a financial engineer in the widest sense (Abdul-Jabbar, 2017). However, the majority of practitioners only use the phrase to describe someone who has received a thorough education in modern finance tools and whose work is based on financial theory

Product Engineering: The process of developing a system, assembly, or device so that it may be produced as a product via a product manufacturing process is known as product engineering. Costs, production, quality, performance, dependability, serviceability, anticipated lifespan, and user features are frequently addressed in product engineering operations. Product engineering operations frequently deal with production, quality, performance, dependability, serviceability, anticipated lifespan, and user features (Al-Araji et al., 2020). In an effort to make the finished product appealing to the market for which it is intended as well as a substantial contribution to the organization's firm, all of these product aspects are frequently pursued. It includes the creation of the product, its design, and the transition to manufacturing.

The knowledge and application of the underlying laws and principles of nature, or "process engineering," enables people to convert raw materials and energy into large-scale, socially beneficial goods. Process engineers have the ability to create techniques for synthesizing and purifying large amounts of desired chemical products by employing the natural forces that govern nature, such as temperature, pressure, concentration gradients, and the law of conservation of mass (Abdullah & Karim, 2021). The main focus areas of process engineering include chemical, physical, and biological process design, implementation, control, optimization, and intensification. The industry sectors that are included in the phrase "agricultural" are automotive, biotech, chemical, culinary, mining, nuclear, petrochemical, pharmaceutical, and software development, among many others.

Financial Solution Engineering: Many businesses need help with the things they sell. They may be competitive rates that enable them to take up a certain niche in the marketplace, or they might be solutions that assist them in meeting their solvency obligations. Financial engineering services (FES) have important expertise about how insurance firms may exploit the abilities of other market participants, particularly reinsurers, to assist them in gaining a competitive advantage in their target markets. How to pay for the often high development expenditures that would be necessary to bring goods to market is a crucial necessity and occasionally a challenge experienced by many of our clients. Clients have access to options that enable them to cover both the initial expenses of creation and continuing the costs of distribution (Chen et al., 2022; Kiprotich & Onsomu, 2021).

Human Efficiency and Productivity Engineering: Productivity engineering is carried out with the help of productivity science. It indicates that productivity science offers the chance to create and patent fresh product features and operational elements that would boost productivity. Science does not usually come before inventions (Ibraheem, 2013; Iman et al., 2019). The development of engineering gadgets by innovators frequently occurs despite the lack of scientific backing. The design of air conditioners to meet different demands is an example of an innovation that occurred first, followed by scientific advancement.

2.2. Artificial Intelligence

The use of AI in service organizations increases profitability and aids in maximizing and identifying sales opportunities. AI also boosts productivity by helping the company perform well, reduce time, and boost operational efficiency (Acemoglu & Restrepo, 2018). It analyses enormous volumes of data more quickly. Askary, Abu-Ghazaleh, and Tahat (2018) provide sage guidance and assistance when required, speeding up decision-making. Chukwudi, Echefu, Boniface, and Victoria (2018) noted that AI assists in customer service by preventing errors, preventing human error, predicting consumer behaviour, and providing greater client satisfaction with a more individualized experience. AI has the ability to alter how your company operates; it is evolving quickly and can provide some unexpected difficulties (Desi, Akintoye, & Aguguom, 2023; Faccia et al., 2019). AI manages massive amounts of data to better understand consumer expectations and wants. One of the hardest difficulties in customer service is striving to meet the ever-higher expectations of customers. Even when you're doing a great job, it's never enough. Being customized is not always simple. The bulk of customer service software programs on the market today are designed to provide reactive support and help customers while they are having problems. According to Luo, Meng, and Cai (2018) and Beura, Naveen, Prusty, Nanda, and Rout (2023), AI has the potential to be a powerful tool for proactive problem-solving and support.

Data Mining Services: Data mining, also known as database discovery of knowledge, is the nontrivial extraction of underlying, originally unidentified, and potentially usable information from data in artificial intelligence and machine learning (Gunning & Aha, 2019). Large databases may be searched for trends and other linkages using statistical approaches. The availability of enormous amounts of data and the need to transform that data into knowledge and information are the main factors that have drawn attention to data mining. Applications for the acquired knowledge include risk management, company management, manufacturing control, market analysis, engineering, and scientific investigation (Sirait, Rosalina, & Sari, 2023).

Credit Evaluation/Scoring Application: When AI is used for credit scoring and lending decisions, it's possible to make decisions based on data, focus on increasing margins instead of lowering risks, and estimate a smoother risk vs. profit curve instead of using pre-calculated scorecard brackets. Most financial institutions still use the scorecard technique, or the dynamics prevalent at the time of its creation, to run credit rating models (Arli et al., 2021; Hamadneh et al., 2021; Hye, 2022). To be regarded as "scorable," a prospective borrower must have a significant amount of historical information on prior borrowing behaviour. Even creditworthy consumers are refused access to credit when this kind of historical information is not available, which is common for new clients in the banking industry.

Algorithmic Trading: In order to take variables like price, timing, and volume into account when executing orders, algorithmic trading uses automatic and pre-programmed trading instructions. An algorithm is a set of instructions for solving a problem. Computer algorithms eventually send smaller portions of the complete order to the market (Hentzen et al., 2022). Algorithmic trading makes decisions regarding whether to buy or sell financial instruments on an exchange using complex formulas, mathematical models, and human monitoring. Algorithmic traders commonly use high-frequency trading technology, which enables a business to carry out tens of thousands of deals per second. There are numerous applications for algorithmic trading, including order execution, arbitrage, and trend trading strategies.

Robotics and Machine Learning: In the modern world, artificial intelligence and machine learning are as prevalent as electricity; therefore, their usage in robotics is also growing in importance (Karim et al., 2022). Using sophisticated machine learning techniques, robots are being trained, and their precision is being strengthened. Robots may be taught using artificial intelligence how to do activities that require them to interact with their environment, such as grasping objects, comprehending spatial relationships, computer vision, motion control, and other tasks (Khemakhem, Ellouzi, Ltifi, & Ayed, 2020).

The development of an employee's emotional intelligence and knowledge begins on the inside as they grow emotionally. In addition to spending time developing your self-awareness, self-regulation, motivation, empathy, and social skills, it also entails acknowledging the different facets of your emotions and feelings. Being able to assist people in difficult circumstances, respectfully voice concerns, and offer solutions that can be agreed upon are all necessary for effective conflict management at work (Kruse, Wunderlich, & Beck, 2019). EI will help. Finding areas of agreement helps leaders who try to comprehend different points of view settle disagreements. Emotional intelligence (EI) is a significant predictor of an individual's capacity to handle stress, form and sustain cooperative relationships, make wise judgments, and deal with constant change, according to studies by Kokina and Davenport (2017) and Kruse et al. (2019).

2.3. Theoretical Review

A group of theorists created the unified theory of technology adoption and utilization. But Venkatesh, Morris, Davis, and Davis (2003) joint and expanded research, furthering the theory's boundaries and introducing them to literature. The unified theory of technology acceptance and use aims to make clear users' intents to accept and utilize information technologies, as well as the ensuing usage behaviour. The theory's proponents contended that there must be a common knowledge of the creation, use, and effects of information technology, as well as other factors that are also covered in the fields of sociology, economics, and psychology. DeLone and McLean (2004) and Seddon (1997), two prominent proponents of the theory, made an effort to compile a summary of the important information system theories that were being used at the time and gave the unified theory of technology acceptance and usage a high ranking among the others. The study emphasized the importance of the theory since it gave researchers a single source from which to conduct future research and a platform on which to assess various ideas as a whole.

Therefore, performance expectation, effort expectation, social influence, and enabling factors are all direct predictors of information technology usage behaviour, according to Venkatesh et al. (2003) assumptions of the unified theory of technology adoption and use. The user's acceptance of utility and usability are important factors in technology acceptance and adoption, according to the unified theory of technology acceptance and usage. DeLone and McLean (2004), on the other hand, noted some limitations in the scope and variety of the theory in information system research. They also noted that information technology is so varied. No single book source has attempted to link all of the theories into a single, coherent presentation of information system theory.

2.4. Artificial Intelligence and Financial Engineering

Chen et al. (2022) studied financial engineering from the point of view of the significance and benefits of the performance of selected units sampled in the study. The study deployed qualitative data based on the primary data collected from the respondents. Using descriptive statistics and inferential analysis, the regression analysis revealed that financial engineering plays a significant role in the sampled companies. The study further showed that while financial engineering was a welcome development, it had a significant positive effect on the performance of the companies tested in the study.

Omoge et al. (2022) studied the application of disruptive technologies and artificial intelligence in financial engineering in the banking sector in developing economies. The study employed a survey research design, using primary data collected with the help of interviews and questionnaires. A total population of 1,450 was collected through a combination of questionnaires and interviews, while 850 sample sizes were retrieved from respondents drawn from the banking sector of the emerging markets. A regression analysis conducted revealed that the application and adoption of disruptive technologies and artificial intelligence significantly and positively affected financial engineering in the banks sampled in the study. Similarly, Abdullah and Karim (2021) used data sourced from primary data to test the effect of financial engineering on obtaining effective financial innovations and corporate performance in achieving set goals. The administered questionnaires aided in harvesting the respondents perceptional responses, and the regression conducted showed that effective application and implementation of product engineering brought a turnaround to the efficiency of the employees. In addition, the study found that financial engineering had a significant effect on corporate performance as a result of new innovations and technological changes in the company.

Al-Sayyed et al. (2021) looked into how artificial intelligence technologies affected financial engineering from the perspective of auditing evidence. Primary data from respondents' structured interviews was used in the study's survey research methodology. Multivariate analysis and descriptive statistics were used to regress the number of interviews that were done. The examination's conclusion demonstrated that artificial intelligence technologies had a favorable impact on efficient audit procedures, which raised the financial quality of the financial reports that the auditors certified. The potential effects of applying financial engineering to the financial performance of certain deposit banks that fall under the categories of savings and credit cooperative financial institutions were also examined by Kiprotich and Onsomu (2021).The study employed structured questionnaires and survey-based field research methods. Workers at 163 cooperative financial institutions in Kenya, of which 45 institutions made up the study's sample size, made up the population of the research. The three measures of financial engineering that were adopted—product, process, and financial solution engineering—were subjected to a regression analysis in this study. While process engineering had a considerable beneficial impact on the organizations' financial performance, the study also found that both product engineering and financial solution engineering had a negative impact.

Al-Araji et al. (2020) study the effect of financial engineering on the ability of the company's strategic plans to hedge and avert financial risks and their implication on the financial performance of the companies sampled in the study. Islamic financial institutions were sampled in the study. The data were extracted from the responses of the Islamic banks based on the research questionnaires administered to a selection of the banks. Consequent to the regression analysis, the study found that financial engineering using information technology had a significant effect on the risk management and financial performance of the Islamic banks tested in the study. Similarly, Neha and Viswanathan (2019) studied disruptive technologies and their implications for corporate re-engineering and performance. The study deployed content analysis using fuzzy logic analysis to create a workforce challenge index for the study. According to an analysis conducted, the study found that disruptive technologies and the use of artificial intelligence had a significant effect on the corporate performance and efficiency of the workforce in the banks considered in the study.

Similarly, Sean (2018) took into account the effects of artificial intelligence on the financial innovations of particular service organizations when analyzing the digitalization of business transactions through the use of blockchain and AI. The study investigated the use of a structured questionnaire in survey field research to get data from a subset of respondents. The findings showed that the financial operations of the organizations under examination benefited greatly from the application of blockchain, artificial intelligence, and cloud accounting, resulting in favorable stakeholder returns that benefited investors and other invested interest groups. Furthermore, Ngure et al. (2017) examined the impact of product engineering on the business performance of loan and savings organizations in Kenya's Kirinyaga County. The research utilized primary data obtained from self-structured questionnaires given to employees of the savings and credit cooperative in Kirinyaga County, Kenya. For the study, multiple regression and descriptive analyses were performed on the retrieved questionnaires. The results of the analysis showed that product engineering had a noteworthy impact on the success of the businesses examined in the study.

3. METHODOLOGY

With the help of triangular research method, the study used both qualitative and quantitative research methods. It also used a mix of secondary and primary data, with respondents filling out structured questionnaires to provide primary data and annual financial reports from service companies providing secondary data. In exploring a combination of quantitative and qualitative research, the study increases the credibility and validity of research findings consistent with prior studies (Marx & Burroughes, 2019; Ugabi & Ugal, 2009). This is coming from the strength of the applicability of artificial intelligence as one of the new innovations and technologies in the contemporary digital economies and global business world that have gone digital in financial preparation and reporting, using artificial intelligence to impact financial engineering usefulness in corporate business activities. This creates customer-oriented products and services in a speedy, accurate, and innovative manner, as well as equipping managers and investors for on-the-spot investment decisions. The study proposes to employ a self-structured questionnaire that would be administered through online platforms (for example, survey money, Google Forms, and face-to-face administration).

A total of 23 listed service companies in the financial sector would form the population of respondents from the part of Nigeria having access to the Internet among the strata practicing accounting firms and practicing accountants in the service companies with a clear understanding of the dynamics and good knowledge of artificial intelligence application and capabilities in solving financial engineering-related issues. The study proposes to employ Yaro Yamane to estimate and determine the appropriate sample size for the study.

Using Yaro Yamane formula:

$$N=n/1+n(\varrho)^2$$

Where

N = Population; n = Sample size; ϱ = Level of significance

3.1. Reliability of Instrument

The pre-test, reliability, and validity of the instrument would be carried out using appropriate tests, including Cronbach Alpha. For the descriptive statistics, some tests like the Hausman tests, Heteroskedasticity test, and Normality test would be carried out for the study. Acceptance or rejection of the specified model or hypotheses would be based on a 5% significance level. The results of the re-test would confirm the validity and reliability of the instrument. The study presents the measurement of the variable in Table 1.

Table 1. Measurement of variables.

Variables	Abbrev.	Measures	Sources
Dependent variables			
Product engineering	PDEN	This would be measured in terms of the adoption of new financial products and services	Kiprotich and Onsomu (2021)
Process engineering	PREN	In terms of the improvement of operational processes	Kiprotich and Onsomu (2021)
Financial solution engineering	FISE	Measured by new ways of solving financial-related problems.	Kiprotich and Onsomu (2021)
Human efficiency & productivity engineering	HCPE	Revenue minus (-) Cost of Revenue /Employee Cost	Kiprotich and Onsomu (2021)
Independent variables			
Data mining services	DESA	Structured questionnaires	
Credit evaluation/Scoring applications	CESA	Structured questionnaires	
Algorithms trading	ALML	Structured questionnaires	
Robotics and machine learning	ROML	Structured questionnaires	
Employees' emotional intelligence/Knowledge	EEIK	Structured questionnaires	

3.2. Model Specification

The study used the employed the following regression model consisted with the study of Kiprotich and Onsomu (2021).

$$Y_i = \alpha_0 + \beta_i + \mu_i \qquad (1)$$

3.3. Functional Relationship

The study functional relationship is presented as follows:

$$FENG = f(DESA, CESA, ALML, ROML, EEIK) \qquad (2)$$

3.4. Models Specifications

The model specifications are presented thus:

$$PDEN_i = \alpha_0 + \beta_1 DESA_i + \beta_2 CESA_i + \beta_3 ALML_i + \beta_4 ROML_i + \beta_5 EEIK + \mu_i \qquad \text{Model 1}$$

$$PREN_i = \alpha_0 + \beta_1 DESA_i + \beta_2 CESA_i + \beta_3 ALML_i + \beta_4 ROML_i + \beta_5 EEIK + \mu_i \qquad \text{Model 2}$$

$$FISE_i = \alpha_0 + \beta_1 DESA_i + \beta_2 CESA_i + \beta_3 ALML_i + \beta_4 ROML_i + \beta_5 EEIK + \mu_i \qquad \text{Model 3}$$

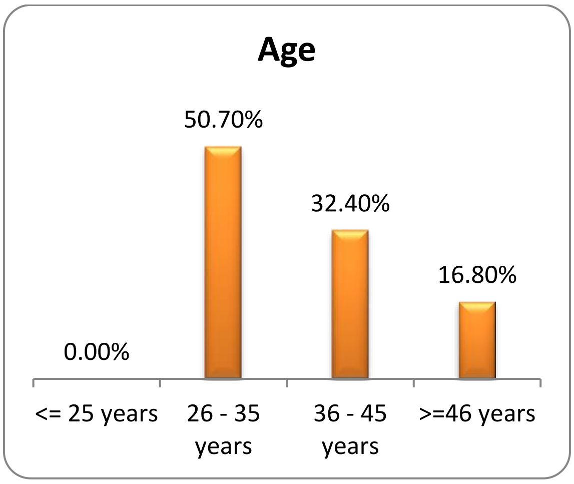
$$HCPE_i = \alpha_0 + \beta_1 DESA_i + \beta_2 CESA_i + \beta_3 ALML_i + \beta_4 ROML_i + \beta_5 EEIK + \mu_i \qquad \text{Model 4}$$

Where: PDEN = Product engineering, PREN = Process engineering, FISE = Financial solution engineering, HCPE = Human efficiency & productivity engineering, DESA = Data mining services, CESA = Credit evaluation/scoring applications, ALML = Algorithms trading, ROML = Robotics and machine learning, EEIK = Employees' emotional intelligence/knowledge.

4. DATA ANALYSIS AND RESULTS

4.1. Descriptive Statistics

The results in Figure 1 present frequency and percentage distributions for the variables age, work experience, educational qualification(s), and professional qualification(s) of a sample of 487 individuals. The data set consists of 487 observations, and the results show that the majority of respondents fall under the age category of 26-35 years (50.7%) and have work experience of 7-10 years (56.7%). The educational qualifications of the respondents are diverse, with M.sc or M.Phil being the most common (65.3%), followed by others (27.3%). Professional qualifications are split evenly between ACA/ACCA/ACMA/ACTI/COREN/ANAN (48.9%) and others (51.1%).



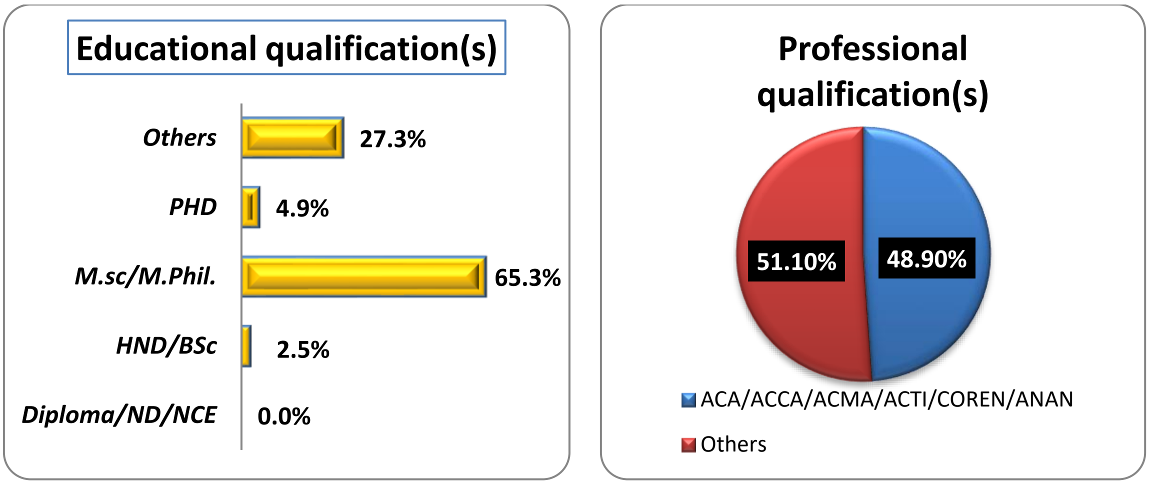


Figure 1. Demographics characteristics.

Note: PhD = Doctors of Philosophy, M.Sc. = Master of Science, M/Phil =Master of Philosophy, HND = Higher Diploma, BSc = Bachelor of Science, ND = National Diploma, NCE = National Certificate of Education, ACA = Associate of Institute of Chartered Accountants of Nigeria, ACCA = Associate of Certified Accountants, Chartered Management Accountants, ACTI = Associate of Chartered Institute of Taxation of Nigeria, COREN = Council of the Regulation of Engineering in Nigeria, ANAN = Association of National Association of Nigeria.

4.2. Financial Engineering

The presented output in Table 2 provides a snapshot of the responses to a survey related to financial engineering practices in the organization. The output contains the frequency counts and percentages of the responses, along with the total number of responses and the mean and standard deviation values.

Table 2. Financial engineering.

Variable	No (%)	Undecided (%)	Yes (%)	Total (%)	Mean [Standard deviation - SD]
Product engineering					
Adoption of customer-oriented and international organization for standardization (ISO) certification for product quality and safety	11 (2.3)	10 (2.1)	466 (95.7)	487 (100)	2.93 [0.33]
Evidence of higher turnover consequent to product engineering practices in the listed service companies in Nigeria	5 (1)	8 (1.6)	474 (97.3)	487 (100)	2.96 [0.24]
Process engineering					
There is an improved practice of digitalization and paperless process services in the listed service companies in Nigeria	17 (3.5)	9 (1.8)	461 (94.7)	487 (100)	2.91 [0.39]
The service companies use electronic devices in customers as much as possible in service rendering	2 (0.4)	9 (1.8)	476 (97.7)	487 (100)	2.97 [0.19]
Financial solution engineering					
The listed companies have in place new innovations to ease cash management and optimal resource utilization.	38 (7.8)	8 (1.6)	441 (90.6)	487 (100)	2.83 [0.55]
The accounting units are fully computerized to enhance the quality of financial reports in adding economic value to the stakeholders.	31 (6.4)	16 (3.3)	440 (90.3)	487 (100)	2.84 [0.51]
Human efficiency and productive engineering					
Evidence of employee welfare satisfaction and career development	23 (4.7)	18 (3.7)	446 (91.6)	487 (100)	2.87 [0.46]
Robust training and fair play in recruitment and employee disciplinary policies	42 (8.6)	2 (0.4)	443 (91)	487 (100)	2.82 [0.56]

Each response category's mean value, which runs from 2.82 to 2.97, shows that respondents had a generally positive opinion of the financial engineering practice in the organization. The SD values range from 0.19 to 0.56, showing that the responses within each category are generally consistent. According to statistical data, the mean values imply that respondents have a favourable opinion of the organization's performance. The standard deviation values, however, imply that there might be some variation in the answers given for each group. Overall, the results show that respondents have a positive opinion of the financial engineering practice linked to product engineering, process engineering, financial solution engineering, human efficiency, and productive engineering. This conclusion is supported by the significant number of "yes" replies and the mean values above.

4.3. Artificial Intelligence

Table 3 displays the results of a survey on financial engineering in publicly traded service businesses using artificial intelligence (AI). Number codes 1 through 5 designate the response categories: Strongly Disagree (SD), Disagree (D), Undecided (U), Agree (A), and Strongly Agree (SA). For each category, the estimated frequency counts and reply percentages are displayed in the second through sixth columns. The mean and standard deviation are displayed in the eighth column, while the total count and percentage are displayed in the seventh.

The results suggest that AI has a positive effect on financial engineering in listed service companies. In each category, the highest percentage of responses was either Agree or Strongly Agree. The lowest percentage of responses was either Undecided or Strongly Disagree. Among the four categories, the highest percentage of responses was Agree, followed by Strongly Agree, Undecided, and Disagree. This implies that the majority of respondents were positive about the effect of AI on financial engineering in listed service companies. Regarding statistical values, the mean values for each category ranged from 3.69 to 4.52, with an overall mean of 4.02. This indicates that, on average, respondents agreed that AI has a positive effect on financial engineering in listed service companies. The standard deviation values for each category ranged from 0.73 to 1.28, with an overall standard deviation of 1.03. These values suggest that there was a moderate degree of variability in responses across the categories. Overall, the results suggest that AI has a positive effect on financial engineering in listed service companies, according to the respondents, as shown in Table 3.

Table 3. Artificial intelligence (AI).

Variables	SD (%)	D (%)	U (%)	A (%)	SA (%)	Total (%)	Mean [SD]
Data mining service							
The listed companies are familiar with Artificial intelligence	22 (4.5)	31 (6.4)	121 (24.8)	210 (43.1)	103 (21.1)	487 (100)	3.7 [1.02]
Artificial intelligence (AI) through data mining services increases financial engineering in the listed service companies	0 (0)	28 (5.7)	53 (10.9)	161 (33.1)	245 (50.3)	487 (100)	4.28 [0.87]
AI solutions using data mining services enhance decisions making, using timely and accurate processed and stored data enhancing financial engineering in the listed service companies	9 (1.8)	37 (7.6)	132 (27.1)	141 (29)	168 (34.5)	487 (100)	3.87 [1.03]
Data mining services of AI help the top management in taking strategic investment decisions	50 (10.3)	34 (7.0)	93 (19.1)	150 (30.8)	160 (32.9)	487 (100)	3.69 [1.28]
Credit evaluation or scoring applications							
AI enhances credit evaluation and age analysis scoring applications in listed service companies	21 (4.3)	41 (8.4)	127 (26.1)	171 (35.1)	127 (26.1)	487 (100)	3.7 [1.08]
Ai is able to support corporate planning and debt management profile	19 (3.9)	23 (4.7)	98 (20.1)	123 (25.3)	224 (46)	487 (100)	4.05 [1.1]
AI solution using Credit evaluation and scoring applications improves financial engineering in the listed service companies.	16 (3.3)	54 (11.1)	85 (17.5)	141 (29)	191 (39.2)	487 (100)	3.9 [1.14]
AI solutions adopt credit evaluation and scoring applications to affect financial engineering	26 (5.3)	18 (3.7)	77 (15.8)	155 (31.8)	211 (43.3)	487 (100)	4.04 [1.1]
Algorithms trading							

Variables	SD (%)	D (%)	U (%)	A (%)	SA (%)	Total (%)	Mean [SD]
Artificial intelligence is characterized by algorithms trading ability to affect financial engineering in listed service companies	0 (0)	12 (2.5)	38 (7.8)	122 (25.1)	315 (64.7)	487 (100)	4.52 [0.74]
AI's algorithms trading operation affects effective financial engineering in listed service companies.	8 (1.6)	33 (6.8)	64 (13.1)	148 (30.4)	234 (48.0)	487 (100)	4.16 [1.0]
Algorithms trading activities of AI improve the financial engineering goals of listed service companies	0 (0.0)	6 (1.2)	52 (10.7)	127 (26.1)	302 (62.0)	487 (100)	4.49 [0.73]
AI solution using algorithms trading has the capacity to enhance financial engineering in the listed service companies	0 (0)	12 (2.5)	90 (18.5)	183 (37.6)	202 (41.5)	487 (100)	4.18 [0.82]
Robotic and machine learning							
The application of robotic and machine learning automatically addresses the problem of financial engineering	20 (4.1)	54 (11.1)	80 (16.4)	192 (39.4)	141 (29)	487 (100)	3.78 [1.11]
AI is compatible with robotics and machine learning in improving the financial engineering objectives of listed service companies	15 (3.1)	41 (8.4)	104 (21.4)	84 (17.2)	243 (49.9)	487 (100)	4.02 [1.15]
Financial engineering is influenced by the application of robotic and machine learning in the listed service companies	23 (4.7)	21 (4.3)	75 (15.4)	219 (45.0)	149 (30.6)	487 (100)	3.92 [1.03]
The interface of the robotic and machine learning in AI solutions automatically upgrades files in enhances financial engineering in listed service companies	15 (3.1)	18 (3.7)	69 (14.2)	90 (18.5)	295 (60.6)	487 (100)	4.3 [1.04]
Employee emotional intelligence							
Employee emotional intelligence significantly affects financial engineering in selected listed service companies	7 (1.4)	10 (2.1)	75 (15.4)	189 (38.8)	206 (42.3)	487 (100)	4.18 [0.87]
Employee emotional intelligence is significant in AI in affecting the functionality of financial engineering in listed service companies	6 (1.2)	10 (2.1)	83 (17.0)	157 (32.2)	231 (47.4)	487 (100)	4.23 [0.89]
Financial engineering and AI in the listed service companies can affect management decisions making in financial engineering	0 (0)	10 (2.1)	47 (9.7)	138 (28.3)	292 (60.0)	487 (100)	4.46 [0.75]
Employee emotional intelligence affects productivity in financial engineering	12 (2.5)	26 (5.3)	89 (18.3)	161 (33.1)	199 (40.9)	487 (100)	4.05 [1.01]

Table 4. Regression analyses.

Variables	(1) PEDN			(2) PREN			(3) FISE			(4) HCPE		
	Coef.	**Se**	**p-val**	**Coef.**	**Se**	**p-val**	**Coef.**	**se**	**p-val**	**Coef.**	**se**	**p-val**
DESA	0.029**	0.013	0.023	0.075***	0.028	0.007	0.094***	0.032	0.003	0.085***	0.030	0.005
CESA	0.015	0.014	0.269	0.024	0.028	0.376	0.154***	0.031	0.000	0.246***	0.036	0.000
ALML	0.141***	0.027	0.000	0.099***	0.033	0.002	0.104***	0.031	0.001	0.252***	0.037	0.000
ROML	0.024	0.015	0.120	0.057***	0.022	0.009	0.084***	0.027	0.002	-0.039	0.027	0.156
EEIK	0.064	0.042	0.130	-0.017	0.028	0.537	-0.074**	0.030	0.014	-0.069**	0.035	0.047
Constant	1.801***	0.262	0.000	1.969***	0.202	0.000	1.388***	0.159	0.000	0.908***	0.183	0.000
Observations	487			487			487			487		
R-squared	0.211			0.258			0.424			0.452		
F-test	6.968			6.552			67.73			36.03		
Prob > F	0.000			0.000			0.000			0.000		
Het.tests [P-value]	803.57 [0.000]			822.50 [0.000]			129.94 [0.000]			283.06 [0.000]		

Note: Data mining services (DESA), Credit evaluation/Scoring applications (CESA), Algorithms trading (ALML), Robotics and machine learning (ROML), and employees' emotional intelligence/Knowledge (EEIK), *** p<0.01, ** p<0.05.

4.4. Regression Analysis

The given results in Table 4 present the outcomes of multiple regression models investigating the relationship between four dependent variables-Product Engineering (PDEN), Process Engineering (PREN), Financial Solution

Engineering (FISE), and Human Efficiency and Productivity Engineering (HCPE)-and five explanatory variables-data Mining Services (DESA), Credit Evaluation and Scoring Applications (CESA), Algorithms Trading (ALML), Robotics and Machine Learning (ROML), and Employees' Emotional Intelligence and Knowledge (EEIK)-with a total of 487 observations. The regression analysis is presented in Table 4.

4.5. Interpretations

The estimated coefficients of the independent variables suggest that DESA has a statistically significant positive relationship with PDEN (0.029, p = 0.023), PREN (0.075, p = 0.007), FISE (0.094, p = 0.003), and HCPE (0.085, p = 0.005) within the 5% and 1% conventional levels. CESA has a non-significant positive relationship with PDEN (0.015, p = 0.269) and PREN (0.024, p = 0.376), but the relationships are significant with FISE (0.154, p = 0.000) and HCPE (0.246, p = 0.000) at 1% level. ALML has a significant positive relationship with all the dependent variables (ranging from 0.099 to 0.252, p<0.01) at the 1% level of significance. ROML has non-significant positive and negative relationships with PDEN (0.024, p=0.120) and HCPE (-0.039, p=0.156), respectively, but a significant positive relationship with FISE (0.057, p=0.009) and HCPE (0.084, p=0.002) at the 1% level. Likewise, ROML has non-significant positive and negative relationships with PDEN (0.064, p=0.130) and PREN (-0.017, p=0.537), respectively, but a significant negative relationships with FISE (-0.074, p=0.014) and HCPE (-0.069, p=0.000) at 5% level.

The R-squared values indicate that the model explains only 21.1%, 25.8%, 42.4%, and 45.2% of the variance in PDEN, PREN, FISE, and HCPE, respectively. The F-statistics for the overall significance of the model are significant for all the models, suggesting that the model explains a moderate proportion of the variance in the dependent variables, and the independent variables collectively explain the variation in the dependent variables. The results also show evidence of heteroscedasticity for the entire model, hence; robust standard error was used. Overall, the use of Data Mining Services (DESA) and Algorithms Trading (ALML) increase Product Engineering (PDEN). However, the use of Credit Evaluation/Scoring Applications (CESA) increases Financial Solution Engineering (FISE), and Human Efficiency & Productivity Engineering (HCPE) while the use of Machine Learning (ROML) reduces Process Engineering (PREN) and Financial Solution Engineering (FISE). The results as reported were consistent with prior studies (Al-Sayyed et al., 2021; Chen et al., 2022; Kiprotich & Onsomu, 2021). In addition, the studies by Omoge et al. (2022); Abdullah and Karim (2021); Al-Araji et al. (2020) and Ngure et al. (2017).

5. CONCLUSION

The current study examines how financial engineering might change as a result of artificial intelligence. In the study, four models were taken into account. The study employed descriptive statistics and inferential analysis (qualitative and quantitative). Each response category's mean value, which runs from 2.82 to 2.97, shows that respondents had a generally positive opinion of the financial engineering practice in the organization. The SD values range from 0.19 to 0.56, showing that the responses within each category are generally consistent. In addition, the result from the descriptive statistics showed that, on average, the majority of the respondents agreed that AI affects financial engineering in listed service companies, with the standard deviation values for each category and the mean values for each category ranging from 3.69 to 4.52, with an overall mean of 4.02. From the regression analysis, the study discovered that product engineering was significantly impacted by artificial intelligence in Model 1. The study discovered that process engineering was significantly impacted by artificial intelligence in Model 2. The study discovered that the design of financial solutions was significantly impacted by artificial intelligence in Model 3. Finally, model 5 of the study revealed that artificial intelligence has a large impact on worker productivity and efficiency in listed service organizations in Nigeria. The investigation came to the conclusion that artificial intelligence has a good and significant impact on financial engineering.

Based on this, the study recommended that the significance of artificial intelligence in corporate business and financial engineering cannot be underrated. The management of the service companies in Nigeria should consider the predictive ability and accurate estimations of artificial intelligence that bring a broader spectrum of opportunities for innovations in filling digital gaps in line with international standards. The managers should brace for the significance of artificial intelligence in the globalization of business transactions in providing innovative financial solutions, efficiency, and the enhancement of competitiveness in the industry of digital service delivery. The service companies in Nigeria should appreciate that artificial intelligence and its computing capabilities and innovations are required to transform, manage, and estimate the ever-growing information needs of customers in relation to the volume of transactions, the need for standardization, security, confidentiality, and timely analytics of artificial intelligence.

This study provides a different understanding of the applicability and importance of artificial intelligence in the emerging digital literature in Nigeria. In spite of the originality and contribution of this study, some limitations were observed. The researcher tried to locate experts in the service companies who are familiar with artificial intelligence. While only a few service companies have tested the application, fewer companies have a strong desire to acquire and put to use the application and implementation of AI. The study was constrained as only a few companies responded to our questionnaires. Future studies may extend the study to other sectors; manufacturing companies and other firms could be included in future studies.

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Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
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