

Nexus between Artificial Intelligence Applications and Digital Financial Inclusion in South west Nigeria

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Abstract: *As a result of the universal call for increased financial inclusion, especially in developing nations, this study evaluated artificial intelligence's (AI) applications' impacts on digital financial inclusion. Existing studies have largely focused on the effects of AI on fraud detection, personalised banking, customer service in manufacturing, financial services, and tourism sectors, to the exclusion of comprehensive empirical data on how AI affects financial inclusion, especially in the context of rural areas of Southwest Nigeria. The quantitative method of survey was employed in determining how AI-enabled customer service impact financial inclusion and the impact of AI-enabled credit and savings on financial inclusion. Descriptive statistics, confirmatory factor analysis, and regression analysis were used to analyze the data. The study found that advancement in AI's ability to answer customers' routine inquiries and provide online guidance to customers' applications will result in a corresponding level of enhanced performance in the financial institutions' drive for financial inclusion. The study established that an improvement in AI's capacity to effectively disseminate information on available options for savings accounts will significantly enhance financial inclusion in Nigeria. This study concludes that the adoption of AI applications especially in customer service and credit and savings can significantly enhance financial inclusion among the rural dwellers in Southwest Nigeria.*

Keywords: *Artificial Intelligence; Financial Inclusion; Rural Dwellers*

1. Introduction

A sizable section of Nigeria's population still lacks sufficient access to banking services, such as banks, leaving them vulnerable and socially isolated (Wayne, Soetan, Bajepade, & Mogaji, 2020). Studies have revealed that those who are impoverished and reside in rural areas are unknowingly cut off from basic economic, social, and financial services (Atkinson, 2014; Demirgüç-Kunt, Klapper, Singer, & Ansar, 2022). Their general well-being is subpar and falls short of the generally acknowledged worldwide benchmark since they are enduring financial exclusion. The successive Nigerian governments have implemented policies promoting financial inclusion because they understand how important financial inclusion is for citizens and the economy at large.

The first significant effort in this area was the implementation of the rural banking program in the late 1970s (Kama & Adigun, 2013). The policy sought to provide rural residents with banking facilities by opening a bank branch in each local government area across the nation so that they could access financial services. Through Decree No. 22 of 1990, the Federal Government also established the People's Bank of Nigeria in October 1989. The bank's mission reflected financial inclusion by providing loans to less fortunate Nigerians who could not obtain credit from traditional banks. Community banks were licensed in the 1980s to provide simple financial services to community residents. The cash-less economy strategy was launched by the government of Nigeria through the nation's Central Bank in the year 2012 with the goals of lowering the cost of managing cash, boosting the effectiveness of the payments system, and promoting financial inclusion. With the implementation of this cashless policy, customers could easily

make purchases via the internet, at an automated teller machine (ATM), or at manned Points of Sale (POS) using a mobile device, smart cards, Personal Digital Assistants (PDA), and other electronic payment systems, such as debit and credit cards (Bayero, 2015). In order to increase financial inclusion in rural areas, the Central Bank of Nigeria (CBN) also created the Payment Service Banks in 2018; acknowledging that digital finance has enormous potential to provide access in hard-to-reach areas and may be most effective in targeting the youth segment in Nigeria within the ages of 18-25 years with 47 percent of youth financially excluded (Nandan, Kumar, & Koppula, 2021). Of the total national population, 36 percent (38 million people of the adult population) remain unbanked which is only a 0.9 percent drop in the exclusion rate from 2012 to 2020. Furthermore, 81 percent (31 million people) of the total unbanked reside in the rural communities which represents 44 percent of the rural communities. One major impediment to the progress of financial inclusion is that financial institutions and the government have not been able to uncover how the poor rural dwellers can be carried along and included in the formal financial services considering their lack of financial sophistication. This is difficult due to the lack of financial literacy and awareness, low-income/poverty, and proximity of the rural dweller (Nandan et al., 2021; Silva et al., 2022).

It is important to note that some government programs designed to promote financial inclusion have made it easier for financial institutions to connect with some of the previously unbanked population. Through the use of smartphones, banks and fintech firms have made it easier for people to manage their finances, make transfers using mobile apps, and shop for goods at online shops and merchants. As a result, a large portion of the population entered the financial industry to benefit from these advantages. Furthermore, startups were able to develop entirely new business models that required entrepreneurs to use financial technology from home in order to save money, apply for loans, and make payments for goods and services (Ozili, 2021). Technology is one of the success elements that financial institutions employed to be able to achieve this milestone.

Digitalizing financial services can increase efficiency by speeding up payments and lowering the cost of sending and receiving payments with the aid of technology. This is evident in the availability of efficient alternatives in the provision of financial products and services after the adoption of AI-powered financial tools. Achieving financial inclusion and ultimately partaking in the benefits accruable to a financially inclusive economy is beyond the formulation and slapdash implementation of policies, all stakeholders especially the banks, Nigerian government, and other financial institutions must be in tune with the trends of the technological age. A major trend in this regard is the adoption of AI. Thus, AI-based solutions are likely to become a game-changer with significant impacts on increasing rural dwellers' financial access (Kshetri, 2021). Due to the high transaction costs and ineffective procedures involved in making small loans to borrowers like low-income individuals and small businesses, traditional banks are unwilling and hesitant to serve them. Both the market for consumer financial services and how consumers engage with the financial services ecosystem are changing as a result of AI. The rapid changes in consumer preferences for digital financial products made possible by AI, along with maturing AI algorithms, growing AI investment, growing competition, and maturing AI algorithms, have all contributed to this shift. The use of AI by financial institutions in their efforts to promote financial inclusion can have a number of advantages. To start with, AI-based solutions offer a quicker response, which increases customer satisfaction. Leo, a banking chatbot from Nigeria's United Bank for Africa (UBA), assists customers with a variety of transactions (Kshetri, 2021). The response rate is fast and the amount of tasks Leo can complete is beyond the reach of human agents.

Additionally, AI-based solutions can identify and subsequently lessen fraudulent transactions. These fraud detection systems can analyze customer behaviours and transaction patterns to alert a cybersecurity mechanism when unusual activities take place (Mhlanga, 2020). Financial institutions also deploy AI to prevent money laundering; the institutions will save the cost of investigating transactions involving money laundering. Furthermore, AI can significantly lower operating costs for financial institutions by automating tasks that would otherwise require human agents to be involved (Mhlanga, 2020). For instance, the AI-based chatbot used by Ant Group to provide customer service answers 2 to 3 million questions daily. While AI has the potential to improve financial inclusion in rural areas, it is

obvious that rural dwellers lack financial literacy and knowledge (Hasan, Le, & Hoque, 2021). They are not informed as regards the potential benefits of accessing financial products and services such as credit facilities that can enhance their ability to be more productive (Jayanthi & Rau, 2019). Even the government policies and campaigns, institutional efforts to foster financial inclusion by ensuring that rural dwellers are provided with pertinent financial services have not yielded the expected results. In the face of the discussion above, some questions are still left unanswered such as what is the impact of AI solutions on achieving financial inclusion in rural areas? Therefore, this study seeks to evaluate the potency of AI applications in achieving financial inclusion in rural parts of Nigeria, particularly, the Southwest region of Nigeria.

The remaining parts of the article include a literature review and theoretical framework, the development of hypotheses, research materials and methods for the hypotheses testing with the statistical tools, results and discussions, and finally, comprehensive conclusions, limitations of the study, and suggestions for further studies.

2. Literature review and theoretical framework

One of the main topical issues in the early 21st century is financial inclusion (Ratnawati, 2020), and has equally become a tool to achieve more equitable economic growth (Chen et al., 2021; Chinoda & Mashamba, 2021). Even the United Nations (UN), has included it in its main goals, that is, the Sustainable Development Goals (SDGs) with the aim of enhancing global welfare premised on human rights and equality (Kuada, 2019). Similarly, it has become one of the key goals of Central Banks of many developing countries. Financial inclusion has become a critical aspect of policy enunciation over the years (Ratnawati, 2020), because of its link with poverty alleviation, inclusive growth, and social inclusion for the downtrodden in the society (Islam, 2018; Menyelim, Babajide, Omankhanlen, & Ehikioya, 2021). Also, a staggering amount of people across the world, especially in developing countries, are unable to access financial services that can enhance their living conditions. As revealed by the World Bank, about 50 percent of the total population of adults in the world, with more than 70 percent of them residing in developing and underdeveloped countries, are unable to access established financial institutions (Islam, 2018).

Comparatively, of the total Nigerian population, 36 percent remain unbanked. Furthermore, 81 percent of the total unbanked reside in the rural communities (NFIS, 2022). This provides an insight into the extent of financial exclusion in the nation. Thus, the case for more financial inclusion as a practical strategy for reducing or eliminating poverty and other social issues worldwide; that is linking rural residents with formal financial institutions; and cultivating the public perception of financial institutions; is legitimate (Islam, 2018). Being a critical issue and a major objective that developing countries are striving to achieve, it has featured in several academic studies with scholars weighing in on what it connotes (Menyelim et al., 2021).

A key idea in this study is digital finance, which serves as a gateway into the idea of digital financial inclusion. According to several academic definitions, digital finance refers to financial services offered via mobile devices, mobile wallets, personal computers, internet connectivity, or debit or credit cards that are connected to a reliable digital payment network (Shofawati, 2019). Digital finance heavily depends on Internet availability and people without access to the internet are not included. Similarly, those without access to mobile phones or other digital devices cannot use the digital finance (Babarinde et al., 2021). The World Bank defines digital financial inclusion as the use of cost-effective digital technologies to provide formal financial services that are specifically tailored to the needs of demographic groups that are generally underserved and financially excluded (Mhlanga, 2020). Digital financial inclusion is described by Gabor and Brooks (2017), and Manyika et al. (2016) as the merger of cutting-edge technology and traditional financial inclusion. Digital financial inclusion which will revolutionise the lives of those at the bottom of the pyramid was made feasible by the development of information and communication technologies (ICT) and AI (Mhlanga, 2020). Some of issues with traditional financial inclusion are overcome with the use of artificial intelligence (AI) and numerous ICT solutions (Gomber et al., 2017). Several works of literature on AI have revealed that there is no generally accepted definition of AI. However, there is a consensus among AI researchers about what intelligence should do (Enholm,

Papagiannidis, Mikalef, & Krogstie, 2021; Van de Gevel et al., 2013). These include but are not limited to reasoning, learning, planning, and using strategies developed by people, communicating to people in natural human languages, solving difficult tasks and puzzles, making judgment regardless of uncertainties, representing knowledge, which include common sense, and integrating all skills together as an entity to achieve common objectives (Enholtm et al., 2021; Van de Gevel et al., 2013).

The primary purpose of AI was for machines to perform alternative tasks for humans as well as serve humans. AI is penetrating industries with an unprecedented speed, forcing entrepreneurs and business strategists to develop new approaches to doing businesses and creating new value sources. AI has evolved to the point that it can make real-time financial decisions, interact with people, participate in gaming against human beings, and collaborate with them. AI performs repetitive tasks by taking information from the environment, making decisions based on data input and past experiences, and carrying out an action that impacts on the environment. AI takes data from images, video clips, text; act as a machine or software e.g. robot, or chatbox; assesses the data via algorithm and offers AI-driven solutions (Soni, Sharma, Singh, & Kapoor, 2019). In addition, the dependence of humans on AI has increased simply because AI can perform cognitive tasks; and process huge data, and analyse its information by the dint of computers (Shabbir & Anwer, 2018). The increasing popularity of AI has stimulated an increase in spending in different areas of AI, especially investigation, marketing, and production.

This study is anchored on the Vulnerable Group Theory of Financial Inclusion by Ozil Peterson, 2020 and Innovator's Solution Theory (Christensen & Raynor, 2013). The central argument of the vulnerable group theory of financial inclusion is that financial inclusion should be directed towards vulnerable members of the society such as poor people, young people, elderly people, and women who are mostly exposed to financial hardship and difficulties. The Innovator's Solution Theory posits that existing firms need to become disruptors themselves (Christensen & Raynor, 2013). The use of AI largely causes disruptions and eases the operations of things originally done manually. AI also solves problems that appeared impossible to solve such as the powerlessness of rural dwellers to access financial products and services.

3. Development of hypothesis

The role of AI in financial inclusion has been noted in many studies such as Kshetri(2021), Mhlanga (2021), Ozili (2021b), Mhlanga (2020) and Wayne et al (2020). Their studies report varying positive impacts of AI on financial inclusion. The major impacts of the adoption of AI on financial inclusion includes personalised customer services, fraud detection, financial advisory, and improved backend processes among others.

Kshetri (2021), notes that fintech companies are at the fore of the adoption of AI applications to solve financial exclusion. Mhlanga (2021), also confirms in his study that AI and machine learning have a significant impact on credit risk assessments using alternative data sources like public data. This enables lenders to conduct thorough credit risk analyses on potential borrowers, evaluate customer behavior, and then certify the clients' capacity to repay the loans, enabling less advantaged individuals to obtain credit. Mhlanga (2020), further notes that the majority of the financially excluded groups are viewed as high risk due to the lack of a practical method to estimate their creditworthiness using available data, providing context for the use of AI on credit rating. With these perceptions, it is believed that AI, if harnessed properly, can help the government and other stakeholders in the financial or banking industry to achieve financial inclusion in which everyone, regardless of distance, level of literacy, and location, will be able to access financial services.

Another construct of artificial intelligence is AI-enabled customer services. The use of AI has made it possible for banks to use chatbots and Electronic Virtual Assistance (EVA) as relationship managers (Mhlanga, 2020). Through the use of natural language processing, a chatbot can recognise keywords as a customer's request and respond in a coherent message by referring to a database. Applying the deep learning feature of AI, Chatbots can improve their responses every time they are responding to similar customer questions and can also update the database they are pointing to for future reference (Kaplan & Haenlein, 2019; Riedel, Mulcahy, & Northey, 2022). AI-enabled customer service can reduce operation

cost by substituting human customer service (Winer, 2001; Xu & Chi, 2017). This means that financial institutions can now service more people without the constraints of location. Leveraging AI-enabled customer service systems can achieve cost savings and provide a better service experience for customers. The use of AI-enabled customer service can also help to standardise customer experience. Consequently, from the aforementioned, this study hypothesized the following:

H1: AI-enabled customer service has a significant impact on financial inclusion in Southwest Nigeria

H2: AI-enabled credit and saving has a significant influence on financial inclusion in Southwest Nigeria

4. Materials and Methods

The quantitative method of survey was pertinent in this study to examine the effect of AI-enabled credit and savings on financial inclusion and assess the impact of AI-enabled customer service on financial inclusion.

The population of this study includes employees of both international and national licensed banks in Southwest, Nigeria. The Southwest states are Lagos, Oyo, Osun, Ekiti, Ondo, and Ogun. The choice of Southwest states is predicated on the high presence of banks in the geopolitical zone. For example, Lagos state serves as Nigeria's commercial hub (Babajide et al., 2020). Also, in comparison to other states in the nation, the geopolitical zone is credited with having a high spread of deposit money banks and other financial institutions, including Bureau de Change, microfinance banks, mortgage banks, development banks, finance houses, discount houses, pension managers and insurance company (Babajide et al., 2020).

International licensed banks include; Access Bank, First Bank, First City Monument Bank, Fidelity Bank, Guaranty Trust Bank, Union Bank, United Bank of Africa, and Zenith Bank (Akamo, 2021). The national licensed banks comprise Unity Bank, Wema Bank, Eco Bank, Heritage Bank, Citi Bank, Keystone Bank, Polaris Bank, Titan Trust Bank, Sterling Bank, Standard Chartered Bank, and Stanbic IBTC (Akamo, 2021). International licensed banks are institutions authorised by the Central Bank of Nigeria to carry out banking operations in both Nigeria as well as maintaining offshore banking operations in the jurisdiction of their choice. National licensed banks on the other hand are those solitary authorised to carry out banking business operations in every state of the federation of Nigeria.

Considering the geographical makeup of the survey population, the researcher selected a total of 360 respondents, from the population area of the banks in the six states of Lagos, Ogun, Oyo, Ondo, Ekiti, and Osun. The use of 364 respondents as the sample size is pegged on Israel (1992) guideline for choosing a sample size for an unknown population at a 90 percent confidence level and 10% sampling error. The attrition rate was 10% and only 324 data were analysed. Since the population for this study was large, a multi-stage sampling technique was employed to reduce the population to a manageable size.

In the submission of Chauvet (2015), the multi-stage sampling technique is effective when the population is scattered over a heterogeneous area. This technique deals with segmenting units into sub-populations, usually referred to as strata, thereby, using a hierarchical structure of units within each stratum (Jain & Hausman, 2004). In the first stage of stratification from the six Southwest states, the researcher stratified Oyo, Ogun, Lagos, Ekiti, Osun, and Ondo states into Senatorial districts. Oyo State has three senatorial districts, namely Oyo South, Oyo Central, and Oyo North. Ogun East, Ogun Central, and Ogun West make up the senatorial districts of Ogun State. Lagos State has Lagos Central, Lagos West, and Lagos East. In addition, while Ondo State has Ondo South, Ondo Central, and Ondo North, Osun State is made up of Osun Central, Osun West and Osun East. Ekiti State is also made up of three senatorial districts, namely Ekiti North, Ekiti Central, and Ekiti South. Using, the lottery method of random sampling, the researcher selected one (1) senatorial district from each state under study.

Singh and Masaku (2014), described the lottery method of sampling as a situation in which each member of a sampled population in this context is assigned a unique number. The numbers are then thoroughly mixed and shaken in a container, and then, without looking, the researcher selects n numbers. Specifically, the Oyo South, Ogun East, Lagos Central, Ondo Central, Osun West, and Ekiti North were the senatorial districts randomly selected in each state. In the second stage, the researcher further stratified the senatorial districts into local governments. Hence, one (1) local government was randomly selected

from each of the senatorial districts, making a total of six local governments. The randomly selected local governments include Ibadan Northeast, Ijebu East, Surulere, Akure North, Iwo, and Oye local governments.

At the third stage of stratification, the researcher employed the lottery method of simple random to select three wards each from the local government. The selected wards are Ibadan Northeast – (Monatan, OritaBashorun, and Iyankangu) Ijebu East – (Ogbere, Ikija, and Ajebandele); Surulere – (Yaba/Ojuelegba, Coker and Ikate), Akure North – (Ayetoro, Isale Oba I and Mofere) Iwo – (Isaleoba I, Molete II and Gidigbo I) and Oye – (Ilupeju 1, Ire and Ayede North). Furthermore, at the fourth stage, two banks representing an international and national licensed bank were randomly selected from each ward, totaling 36 banks. At the last stage, ten respondents were selected with the aid of systematic sampling technique in each of the randomly selected banks.

The objectives of this research are presented in the model, where financial inclusion is expressed as a function of the components of AI applications such as AI-enabled credit and saving and AI-enabled customer service. In other words, financial inclusion is regarded as the dependent variable while AI-enabled Credit and Saving and AI-enabled Customer Service are the independent variables. The data were analysed using frequency, descriptive statistics, confirmatory factor analysis, and regression analysis. For the reliability test, the study employed the Cronbach’s Alpha test to ascertain the reliability of the items used to measure the constructs of the paper.

5. Results

Table 1: Demographic Characteristics of Respondents

Sex	Frequency	Percentage (%)
Male	164	50.7
Female	160	49.3
Total	324	100.0
Age Groups	Frequency	Percentage (%)
18-- 30 Years	156	48.1
31-- 40 Years	154	47.5
41-- 50 Years	14	4.4
TOTAL	324	100.0
Marital Status	Frequency	Percentage (%)
Single	151	46.6
Married	171	52.8
Separated	1	0.3
Missing	1	0.3
Total	324	100.0
Years of Experience	Frequency	Percentage (%)
1 - 5 Years	261	80.6
6 - 10 Years	59	18.2
11 - 15 Years	4	1.2
TOTAL	324	100.0

Table 1 shows that 164 male employees of the selected banks participated in this survey, and they represent 50.7 percent of the study’s sample size, while 143 female employees of the selected banks participated in the study, and they represent 49.3 percent of the study. A total of 156 respondents are within the age group of 18 and 30 years, and they represent 48.1 percent of the sample size. The result further shows that 171 respondents are married and represent 52.8 percent of the sample size. The table shows that 261 respondents have spent between a year and 5 years in their organisations and they represent 80.6 percent of the study sample size.

Confirmatory factor Analysis – Principal component analysis

AI-Enabled Customer Service

In measuring the AI-enabled customer service in this study, the items used are represented as; AI answering of customer’s routine inquiries (AIECS_1), AI online guidance to customers applications (AIECS_2), AI ability to answer questions on individual customer’s accounts (AIECS_3), AI notification of customers on downtime within operation hours and days (AIECS_4), AI communication on new banking applications, products, and services (AIECS_5), AI communication and transfer of customers’ complaints (AIECS_6), AI regular generation and sending of season greeting messages(AIECS_7), AI customer guidance on banking steps such as account opening (AIECS_8), AI assistance on the processing of loan application (AIECS_9), AI ability to generate follow-up messages to check on customers with incomplete applications(AIECS_10).

Table 2: Factor Analysis of AI-Enabled Customer Service

Factor Analysis of AI-Enabled Customer Service							
	Rotated Component Matrix					Communalities	
	1	2	3	4	Initial	Extraction	
AIECS_1	.936	.024	-.012	-.081	1.000	.883	
AIECS_2	.954	.013	-.019	-.101	1.000	.921	
AIECS_3	.652	.030	-.414	-.311	1.000	.693	
AIECS_4	.091	.013	-.778	.068	1.000	.619	
AIECS_5	-.151	-.054	-.299	.814	1.000	.777	
AIECS_6	-.202	-.104	.383	.771	1.000	.793	
AIECS_7	-.053	.019	.794	.094	1.000	.642	
AIECS_8	-.022	.504	.524	-.335	1.000	.642	
AIECS_9	.018	.917	.011	-.137	1.000	.859	
AIECS_10	.038	.917	-.020	.049	1.000	.846	
Initial Eigen values (Cum%)	28.752	51.352	66.278	76.748	10.000	7.675	
Measure of Sampling Adequacy							
Kaiser-Meyer-Olkin Measure of Sampling Adequacy						0.635	
					Approx. Chi-Square	1424.179	
Bartlett's Test of Sphericity					df	45	
					Sig.	.000	
Extraction Method: Principal Component Analysis							
Rotation Method: Varimax with Kaiser Normalization							
a. Rotation converged in 4 iterations							

Source; Researcher’s estimate with SEM, 2022

The Kaiser-Meyer-Olkin (KMO) statistic was employed by the study to determine the adequacy of the sampling used for the investigation. The statistic computes the proportion of variance in the variables that is attributed to the underlying factors. Greater scores (approaching 1) suggest that factor analysis is imperative for the data, while scores below 0.50 indicate the result obtained using factor analysis may not be very helpful. The Bartlett’s test of sphericity tests the hypothesis to confirm that the correlation matrix is an identity matrix, suggesting that the variables are not related. This makes the variable less vulnerable to structure detection. Small values (not more than 0.05) significance level show that factor analysis is very useful for this study.

The KMO test in Table 2 was carried out on AI-enabled customer service with an estimated score of 0.635; Chi-square distribution (1424.179) and a sphericity test significant at 1 percent level with a degree of freedom (df=45). The result shows that the sample is adequate for factor analysis with a greater

proportion of the original variables' variance accounted for by the components. The principal components analysis (PCA) of AI-enabled customer service in Table 2 shows the initial and extracted communalities, the rotated component matrix, and the KMO and Bartlett's sphericity test for sample adequacy for factor analysis.

The initial and extracted communalities shows the variance in the original variables of AI-enabled customer service attributed to all the components and the variance explained by the respective components. It indicates the initial eigen solution with AIECS_2 (0.921) with the highest variance extract in its component. The extracted variances show that AIECS_3 (0.693), AIECS_4 (0.619), AIECS_7 (0.642), and AIECS_8 (0.642) were below the 70 percent loading coefficient while other variables were satisfactorily loaded. However, given that the rotated component matrix allows for a more even distribution of the variances across the components, it is used in explaining the result of the factor analysis in this study.

The rotated component matrix, which allows for a more even distribution of the extraction communalities, shows that the first component is highly correlated with AIECS_2 (0.954) and also uncorrelated with the other three components. The second component is highly correlated with AIECS_9 (0.917), also it is observed that AIECS_9 is less correlated with the third component than AIECS_10 though both variables exhibit the same proportion of variance in component_2. The third component is highly correlated with AIECS_7 (0.794) while the fourth component is seen to be strongly correlated with AIECS_5 (0.814). This, therefore, suggests that further analysis of AI-enabled customer services can be focused on AIECS_2, AIECS_9, AIECS_10, and AIECS_5. These components accounted for 76.748 percent of the total variance in the AIECS construct indicator.

AI-Enabled Credit and Savings

In measuring AI-enabled credit and savings (AIECRS), 10 items were employed. The first item (AIECRS_1) captures AI's assistance to customers in the opening of accounts after obtaining personal information from them. The second (AIECRS_2) measures AI's ability to inform prospective customers of available savings account options. The third (AIECRS_3) is on AI's ability to follow-up on prospective customers to complete their applications. The fourth (AIECRS_4) focuses on AI's production of credit scores for individual customers. The fifth (AIECRS_5) measures AI's assistance to customers in remembering their weekly commitment to save money AI's provision of a timely savings record for customers and ability to keep track of interest added to customers' savings were captured in the sixth (AIECRS_6) and seventh (AIECRS_7) items. The eighth (AIECRS_8) and ninth (AIECRS_9) items measure AI's guidance to customers in entering into safe and low-risk investments and education of customers on their creditworthiness. The tenth item (AIECRS_10) accounts for the ability of AI to gather data on the rates of withdrawals and deposits in customers' accounts.

Table 3: Factor Analysis of AI-Enabled Credit and Saving

Factor Analysis of AI-Enabled Credit and Saving						
	Rotated Component Matrix				Communalities	
	1	2	3	4	Initial	Extraction
AIECRS_1	.855	.119	-.004	.031	1.000	.746
AIECRS_2	.908	.024	.029	-.159	1.000	.851
AIECRS_3	.673	-.034	-.163	-.405	1.000	.644
AIECRS_4	.148	.200	-.734	.166	1.000	.628
AIECRS_5	-.234	-.022	-.478	.681	1.000	.747
AIECRS_6	-.141	-.180	.121	.857	1.000	.802
AIECRS_7	-.020	-.013	.758	.414	1.000	.747
AIECRS_8	.057	.450	.642	-.116	1.000	.632
AIECRS_9	.060	.925	.016	-.131	1.000	.877
AIECRS_10	.038	.910	-.054	-.030	1.000	.834

Initial Eigen values (Cum%)	27.922	46.977	63.787	75.075	10.000	7.508
Measure of Sampling Adequacy						
Kaiser-Meyer-Olkin Adequacy	Measure of Sampling Adequacy					0.588
					Approx. Chi-Square	1217.801
Bartlett's Test of Sphericity					df	45
					Sig.	.000
Extraction Method: Principal Component Analysis						
Rotation Method: Varimax with Kaiser Normalization						
a. Rotation converged in 5 iterations.						

Source; Researcher's estimate with SEM, 2022

The sampling adequacy for factor analysis was determined using the KMO (0.588; $X^2 = 1217.801$) and the Bartlett's sphericity test (df=45; P-value<0.01). The result (Table 3) shows that 58.8 percent of the sample variance was attributed to underlying factors associated with the construct. The initial communalities indicate the variance in the variables explained by all the components, usually 1.00 for all the variables. The extraction communalities show that AIECRS_9 (0.877) exhibits the highest variance among the variables. Except for AIECRS_3 (0.644), AIECRS_4 (0.628), AIECRS_8 (0.632), all the factors meet the 70 percent benchmark for factor loadings at this stage. The rotated component matrix was employed to examine a more even distribution of the variance and to identify the best components with their associated highest variance that explained AI-enabled credit and savings. As shown, the first component is highly correlated with AIECRS_2 (0.908), the second and third components are strongly correlated with AIECRS_9 (0.925) and AIECRS_7 (0.758) while the fourth component is seen to be mostly correlated with AIECRS_6 (0.857). From the initial eigen values, it is observed that these four components account for the greater proportion (75.075) of the total variances in the AIECRS as a construct measurement for artificial intelligence.

Financial inclusion

Financial inclusion (FI) items in this study are represented as branches of banks in various communities (FI_1), availability of ATM within the communities (FI_2), ownership of active bank accounts by people within the communities (FI_3), possession of personal ATM cards for withdrawals and payments by people within the communities (FI_4), utilisation of bank accounts for savings by people within the communities (FI_5), successful bank loans given to members of the communities (FI_6), frequency of community members to the bank to complete bank transactions (FI_7), availability of varieties of loan products to the community (FI_8), those that have stopped keeping money at home (FI_9), provision of information on account balances to account holders (FI_10) and usage of alternative banking options (FI_11).

Table 4: Factor Analysis of Financial inclusion

Factor Analysis of Financial Inclusion							
	Rotated Component Matrix					Communalities	
	1	2	3	4	5	Initial	Extraction
FI_1	-.033	.807	-.174	-.068	.032	1.000	.689
FI_2	-.004	.914	.010	-.032	-.023	1.000	.837
FI_3	-.014	.553	.567	.038	-.124	1.000	.643
FI_4	.046	-.046	.912	-.051	.031	1.000	.839
FI_5	.087	-.116	.761	-.085	.049	1.000	.609
FI_6	.030	-.040	-.042	-.182	.800	1.000	.678
FI_7	-.086	.014	.083	.270	.689	1.000	.562
FI_8	-.308	-.075	-.049	.778	.101	1.000	.719
FI_9	.278	-.022	-.090	.811	-.047	1.000	.746
FI_10	.936	-.024	-.009	.061	-.030	1.000	.881
FI_11	.909	-.022	.148	-.072	-.021	1.000	.855
Initial Eigen values (Cum%)	28.752	51.352	66.278	76.748	84.489	11.000	8.058
Measure of Sampling Adequacy							
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.						.505	
				Approx. Chi-Square	947.545		
Bartlett's Test of Sphericity				df	55		
				Sig.	.000		
Extraction Method: Principal Component Analysis.							
Rotation Method: Varimax with Kaiser Normalization.							
Rotation converged in 5 iterations.							

Source; Researcher's estimate with SEM, 2022

The sampling adequacy for factor analysis was determined using the KMO (0.505; $X^2 = 947.545$) and Bartlett's sphericity test (df=55; P-value<0.01). The result (Table 4) shows that 50.5 percent of the sample variance was attributed to underlying factors associated with the construct. The initial communalities indicate the variance in the variables explained by all the components, usually 1.00 for all the variables. The extracted variance shows that all the items except FI_1 (0.689), FI_3 (0.643), FI_5 (0.609), FI_6 (0.678) and FI_7 (0.562) loaded above 70 percent benchmark.

The rotated component matrix result shows that the variances in five extracted components of financial inclusion were adequately explained. These components are; FI_10 with estimated variance (0.936) has the highest correlation with component_1, FI_2 (0.914) relates to component 2, FI_4 (0.912) in the third component, FI_9 (0.811) in component_4 and FI_6 (0.800) in the fifth component. Hence, it is seen that five components were used to explain the construct of financial inclusion in the study. These five components accounted for 84.489 total variations in financial inclusion in this study, as indicated by the cumulative percentage of the initial eigen value statistic. The initial and extracted communalities shows the initial eigen solution with FI_10 with the highest variance extract in its component.

Bivariate Factor Regression Results

Table 5: AI-Enabled Customer Service and Financial Inclusion Coefficients

AI-Enabled Customer Service and Financial Inclusion Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.000	.053		-.004	.997
	FAC2_2	.175	.053	.176	3.278	.001
2	(Constant)	-.001	.053		-.010	.992
	FAC2_2	.175	.053	.176	3.307	.001
	FAC1_2	.135	.053	.135	2.546	.011
F-statistic (8.744; P-value=0.000)						
Durbin Waston (1.94)						
a. Dependent Variable: FAC3_1						

Source; Researcher's estimate with SEM, 2022 Factor score 3 for analysis1 (FAC3_1) represents FINC component measure of people with active bank accounts. FAC1_2: AIECS component measuring AI answering of customer's routine enquiries. FAC2_2: AIECS component measuring AI online guidance to customers applications.

Table 5 shows that the statistical model is significant at 1 percent (F-statistic= 8.744; P-value<0.01;) while the Durbin Watson statistic (1.941) confirms the absence of serial autocorrelation among the variables. Evidence from the stepwise estimated coefficient of the factor score for AI-enabled customer service shows that the factor scores 1 (FAC1_2) and 2 (FAC2_2); for analysis 2 (AIECS) had a significant positive effect of 0.135 and 0.176 percent on financial inclusion at 1 percent significance level. The factors score FAC1_2 shows that AI's ability to answer customers' routine and frequently asked questions has improved financial inclusion by 13.5 percent, while FAC2_2 result indicates that AI's online guide to customers about stages of application for a bank's product has significantly enhanced financial inclusion by 17.6 percent. This implies that AI-enabled online guidance to customers applications is empirically proven to be a more effective instrument of AI-induced financial inclusion in this present study compared to other forms of AI-enabled customer services considered in this study. This also shows that there is a significant positive relationship between AI-enabled customer service and financial inclusion such that an advancement in AI-enabled customer services will result in a corresponding level of enhanced performance in financial inclusion drive by the financial institutions.

Table 6: AI-Enabled Credit and Savings and Financial Inclusion Coefficients

AI-Enabled Credit and Savings and Financial Inclusion Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.000	.054		-.006	.995
	FAC2_4	.139	.054	.139	2.576	.010
F-statistic (6.633; P-value =0.010)						
Durbin Watson =1.90						
a. Dependent Variable: FAC3_1						

Source; Researcher's estimate with SEM, 2022. Factor score3 for analysis1 (FAC3_1) represents FINC component measure of people with active bank accounts. Factor score 2 for analysis 4 (FAC2_4) denotes AIECRS component measuring AI enabled information on prospective customers of available saving account options

The analysis of Table 6 shows the relationship between AI-enabled credit and savings measured by the factor score2 (FAC2_4) for analysis 4 as the most significant factor that best explained financial inclusion in this study model. This factor regression (FAC2_4) measured the effect of AI-enabled information on prospective customers of available saving account options. This significant positive influence accounted for 13.9 percent total effect of AI-enabled credit and savings on financial inclusion. The result is confirmed at 1 percent significance level (T-statistic =2.576; P-value=0.010). The result of the F-statistic (6.633; P-value=0.010) measuring the fitness of the data in the financial inclusion model indicates that the estimated model is of good fit and significant at 1 percent while the Durbin Watson (1.90) serial autocorrelation test confirmed the absence of endogenous regressor in the result. This, therefore, implies that AI-enabled credit and savings is a significant determinant of financial inclusion in this study. It is also noted that there is a significant positive relationship between AI-enabled credit and savings and financial inclusion. Thus, an improvement in AI-enabled credit and savings services particularly as it relates to available and dissemination of information on available options for savings accounts will significantly enhance financial inclusion in Nigeria.

6. Discussion

This section discusses the results of the tested research hypotheses. A bivariate factor regression was employed to test the hypotheses. Hypothesis one states that AI-enabled customer service has no significant impact on financial inclusion in Southwest Nigeria. The factor regression result in Table 5 shows that there is a significant positive relationship between AI-enabled customer service and financial inclusion, such that advancement in AI-enabled customer services will result in a corresponding level of enhanced performance in financial inclusion drive financial institutions. Specifically, the AI-enabled customer services measurements are components measuring AI's ability to answer customers' routine inquiries and provide online guidance to customers' applications. Therefore, the null hypothesis is rejected, and the alternative hypothesis that states AI-enabled customer service has a significant impact on financial inclusion in Southwest Nigeria is accepted.

Hypothesis two states that AI-enabled credit and saving has no significant influence on financial inclusion in Southwest Nigeria. The factor regression result in Table 6 shows that the regression weight for AIECRS in the prediction of financial inclusion (FINC) is significantly different from zero at 13.9 percent level. Thus, an improvement in AI-enabled credit and savings services, particularly as it relates to the availability and dissemination of information on available options for savings accounts, will significantly enhance financial inclusion in Nigeria. Therefore, the alternative hypothesis that states that AI-enabled credit and savings has a significant influence on financial inclusion in Southwest Nigeria is accepted, and the null hypothesis is rejected.

The main objective of this research was to examine how AI applications can be used to achieve financial inclusion in Nigeria, especially in the rural areas of the Southwest of the country. The following AI applications were examined to demonstrate the impact of AI applications on financial inclusion. The AI applications investigated in the study are AI-enabled customer service and AI-enabled credit and savings. The empirical evidence from this study shows that AI-enabled customer services (AIECS) and AI-enabled credit and savings (AIECRS) have a significant influence on financial inclusion. These AI applications have been established in previous studies to improve financial services (Belanche et al., 2019; Manser Payne et al., 2021; Mhlanga, 2020). The Central Bank of Nigeria's audacious target to improve the financial inclusion rate from 64.1 percent to 75 percent by 2024 (NFIS, 2022) has necessitated the need for the accelerated adoption of technology (of which AI is a crucial part) in financial services. The study has empirically highlighted areas in which AI features can be adopted for improvement in financial inclusion and a commensurate decline in financial isolation. Previous studies have also identified the AI features that can power the AI applications in financial services, such as the use of natural language processing, AI algorithms, big data analytics, machine learning, and natural data (Ji et al., 2021; Manser Payne et al., 2021).

This study revealed that AI applications have significant impacts on digital financial inclusion. It is therefore suggested that AI applications only be developed based on the outcome of an extensive market survey and research. Market surveys and research will unearth the needs of the general public or any

section of society the applications are meant for. So, it is believed that AI applications developed on a need-basis will serve their intended purposes successfully and satisfactorily. Financial institutions should set up a structure for the research and development of specialized financial products that will serve the excluded group. More specifically, the study revealed that an improvement in AI-enabled credit and savings services, particularly as it relates to the dissemination of information on available options for savings accounts, will significantly enhance financial inclusion in Nigeria, as well as AI-enabled online guidance to customers and AI-enabled automatic responses to customers' routine and frequently asked questions. It is therefore suggested that banks and fintech companies double down and invest in the use of more AI-enabled customer service applications; examples include chatbots, self-services, and agent assistance. By transitioning to a more AI-based solution, the customer service team can assist more people and create a better overall experience.

7. Conclusions, Limitations of the study and Suggestions for further studies

Evident in the findings from this study suggests that the Nigerian business environment is ripe and ready for the adoption of AI and its applications, which could enhance digital financial inclusion in the country. Also, since 81 percent of the Nigerian population owns mobile phones, the foundation for the adoption of technology has been laid. The Nigerian government and regulators can harness this opportunity to foster the adoption of digital financial inclusion, which thrives solely on technologies like AI.

There are several limitations in the current work that should be considered. Firstly, the research needed the willful consent of respondents to complete the questionnaire in order to address the research questions. The respondents expressed their concerns relating to their anonymity and a general fear of the unknown impact of the research on them. The researcher allayed their concerns by providing explanations of the importance of the study. Also, the researcher was able to guarantee the respondents' anonymity. As such, out of the 360 total participants, 324 completed and returned the questionnaire after being persuaded and receiving further education on the purpose of the study. Secondly, for this type of study, a national examination would have been appropriate to arrive at more robust findings, but the study was limited to the southwest region of Nigeria. While the study generated robust findings from the survey instrument from the Southwest region, it is imperative that future studies assess this subject from another perspective by considering the impact of AI applications on financial inclusion in the entire country of Nigeria for more robust findings.

Funding: We appreciate the Covenant University Centre for Research, Innovation and Discovery (CUCRID) for the financial support for this publication.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors declare no conflict of interest

References

1. Akamo. (2021). *Exclusive: Best performing banks in Nigeria judging by the numbers*. Retrieved from nairametrics.com
2. Atkinson. (2014). *Rural-urban linkages: South Africa case study. Territorial Cohesion for Development Program, Rimisp, Santiago*.
3. Babajide, Lawal, A., Amodu, L., Ewetan, O., Esowe, S., & Okafor, T. (2020). *Financial institutions concentration and financial inclusion penetration in Nigeria: a comparative analysis*. *Journal of Contemporary African Studies*, 38(4), 610-626.
4. Babajide, Abiola Ayopo, Oluwaseye, Emmanuel Olayinka, Lawal, Adedoyin Isola, & Isibor, Aregban Akhanolu. (2020). *Financial technology, financial inclusion and MSMEs financing in the south-west of Nigeria*. *Academy of Entrepreneurship Journal*, 26(3), 1-17.

5. Babarinde, Gbenga Festus, Gidigbi, Matthew, Ndaghu, Julius, & Abdulmajeed, Idera. (2021). *Digital finance and the future of Nigerian banking system: a review*. *Nile Journal of Business and Economics*, 6(16), 24-35
6. Bayero, M. A. (2015). *Effects of Cashless Economy Policy on financial inclusion in Nigeria: An exploratory study*. *Procedia-Social and Behavioral Sciences*, 172, 49-56.
7. Belanche, Daniel, Casalo, Luis V, & Flavián, Carlos. (2019). *Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers*. *Industrial Management & Data Systems*.
8. Chauvet, Guillaume. (2015). *Coupling methods for multistage sampling*. *The Annals of Statistics*, 43(6), 2484-2506.
9. Chen, Yanyu, Kumara, E Kusuma, & Sivakumar, V. (2021). *Investigation of finance industry on risk awareness model and digital economic growth*. *Annals of Operations Research*, 1-22.
10. Chima, Menyelim M, Babajide, Abiola Ayopo, Adegboye, Alex, Kehinde, Segun, & Fasheyitan, Oluwatobi. (2021). *The relevance of financial inclusion on sustainable economic growth in sub-saharan African Nations*. *Sustainability*, 13(10), 5581
11. Chinoda, Tough, & Mashamba, Tafirei. (2021). *Fintech, financial inclusion and income inequality nexus in Africa*. *Cogent Economics & Finance*, 9(1), 1986926.
12. Christensen, Clayton, & Raynor, Michael. (2013). *The innovator's solution: Creating and sustaining successful growth*: Harvard Business Review Press.
13. Demirgüç-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). *The global finindex database 2021: Financial inclusion, digital payments, and resilience in the Age of COVID-19*: World Bank Publications.
14. Enholm, Ida Merete, Papagiannidis, Emmanouil, Mikalef, Patrick, & Krogstie, John. (2021). *Artificial intelligence and business value: a literature review*. *Information Systems Frontiers*, 1-26
15. Gabor, Daniela, & Brooks, Sally. (2017). *The digital revolution in financial inclusion: international development in the fintech era*. *New political economy*, 22(4), 423-436.
16. Gomber, Peter, Koch, Jascha-Alexander, & Siering, Michael. (2017). *Digital Finance and FinTech: current research and future research directions*. *Journal of Business Economics*, 87, 537-580.
17. Goyal, K., & Kumar, S. (2021). *Financial literacy: A systematic review and bibliometric analysis*. *International Journal of Consumer Studies*, 45(1), 80-105.
18. Hasan, M., Le, T., & Hoque, A. (2021). *How does financial literacy impact on inclusive finance?* *Financial Innovation*, 7(1), 1-23.
19. Islam, Moynul. (2018). *Implications of Financial Inclusion in a Country's Economic Development: A Study on South Asia (Bangladesh)*.
20. Jain, Aridaman K., & Hausman, Robert E. (2004). *Stratified Multistage Sampling Encyclopedia of Statistical Sciences*: John Wiley & Sons, Inc.
21. Ji, Xuanming, Wang, Kun, Xu, He, & Li, Muchen. (2021). *Has digital financial inclusion narrowed the urban-rural income gap: the role of entrepreneurship in China*. *Sustainability*, 13(15), 8292.
22. Jayanthi, M., & Rau, S. (2019). *Determinants of rural household financial literacy: Evidence from south india*. *Statistical Journal of the IAOS*, 35(2), 299-304.
23. Kama, U., & Adigun, M. (2013). *Financial inclusion in Nigeria: Issues and challenges (CBN Occasional Paper, 45)*.
24. Kaplan, Andreas, & Haenlein, Michael. (2019). *Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence*. *Business horizons*, 62(1), 15-25.
25. Kuada, John. (2019). *Financial inclusion and the sustainable development goals Extending Financial Inclusion in Africa (pp. 259-277)*: Elsevier.
26. Kshetri, N. (2021). *The role of artificial intelligence in promoting financial inclusion in developing countries (Vol. 24, pp. 1-6)*: Taylor & Francis.
27. Manser Payne, Elizabeth H, Peltier, James, & Barger, Victor A. (2021). *Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms*. *Journal of Research in Interactive Marketing*, 15(1), 68-85.

28. Mhlanga, D. (2020). *Industry 4.0 in finance: the impact of artificial intelligence (ai) on digital financial inclusion*. *International Journal of Financial Studies*, 8(3), 45.
29. Mhlanga, D. (2021). *Financial inclusion in emerging economies: The application of machine learning and artificial intelligence in credit risk assessment*. *International Journal of Financial Studies*, 9(3), 39.
30. Nandan, A., Kumar, I., & Koppula, P. (2021). *National Financial Inclusion Strategy (2019-2024): A Review*.
31. Ndung'u, N., & Signé, L. (2020). *The Fourth Industrial Revolution and digitization will transform Africa into a global powerhouse*. *Foresight Africa Report*.
32. Ouachani, S., Belhassine, O., & Kammoun, A. (2020). *Measuring financial literacy: A literature review*. *Managerial Finance*.
33. Ozili, Peterson K. (2020). *Theories of financial inclusion Uncertainty and challenges in contemporary economic behaviour (pp. 89-115): Emerald Publishing Limited*.
34. Ozili, P. K. (2021). *Financial Inclusion in Nigeria: Determinants, Challenges, and Achievements*. *New Challenges for Future Sustainability and Wellbeing*, 377-395.
35. Ratnawati, Kusuma. (2020). *The impact of financial inclusion on economic growth, poverty, income inequality, and financial stability in Asia*. *The Journal of Asian Finance, Economics and Business*, 7(10), 73-85
36. Riedel, Aimee, Mulcahy, Rory, & Northey, Gavin. (2022). *Feeling the love? How consumer's political ideology shapes responses to AI financial service delivery*. *International Journal of Bank Marketing*.
37. Shabbir, Jahanzaib, & Anwer, Tarique. (2018). *Artificial intelligence and its role in near future*. arXiv preprint arXiv:1804.01396.
38. Shofawati, Atina. (2019). *The role of digital finance to strengthen financial inclusion and the growth of SME in Indonesia*. *KnE Social Sciences*, 389-407-389-407.
39. Siddique, M. A., Haq, M., & Rahim, M. (2020). *The impact of the Islamic banking industry on economic growth and poverty reduction in Pakistan*. *Enhancing Financial Inclusion through Islamic Finance, Volume II*, 259-279.
40. Singh, & Masuku. (2014). *Sampling techniques & determination of sample size in applied statistics research: An overview*. *International Journal of economics, commerce and management*, 2(11), 1-22.
41. Silva, A. M. d. A., Lazaro, L. L. B., Andrade, J. C. S., Prado, A. F. R., Ventura, A. C., Campelo, A., & Tridello, V. (2022). *Examining the urban resilience strategy of Salvador, Bahia, Brazil: A comparative assessment of predominant sectors within the resilient cities network*. *Journal of Urban Planning and Development*, 148(2), 05022002.
42. Soni, Neha, Sharma, Enakshi Khular, Singh, Narotam, & Kapoor, Amita. (2019). *Impact of artificial intelligence on businesses: from research, innovation, market deployment to future shifts in business models*. arXiv preprint arXiv:1905.02092.
43. Van de Gevel, Ad JW, Noussair, Charles N, van de Gevel, Ad JW, & Noussair, Charles N. (2013). *The nexus between artificial intelligence and economics: Springer*.
44. Wayne, T., Soetan, T., Bajepade, G., & Mogaji, E. (2020). *Technologies for financial inclusion in Nigeria*. Wayne, T., Soetan, T., Bajepade, G & Mogaji, E., *Technologies for Financial Inclusion in Nigeria. Research Agenda Working Papers*, 2020(4), 40-56.
45. Winer, Russell S. (2001). *A framework for customer relationship management*. *California management review*, 43(4), 89-105.
46. Xu, Xun, & Chi, Christina Geng-qing. (2017). *Examining operating efficiency of US hotels: A window data envelopment analysis approach*. *Journal of Hospitality Marketing & Management*, 26(7), 770-784.