World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Review Article)

Check for updates

Machine learning for financial inclusion in agriculture: A study of AI-based credit scoring tools in rural Nigeria

Babarinde Taofeek Olajide [1,*], Chijioke Cyriacus Ekechi [2], Taoheed Olawale POPOOLA [3], Oguntoye George Adeshina [4], Selasi Ayittey [5] and Peter Chika Ozo-ogueji [6]

[1] *Department of Agricultural Economics, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.*
[2] *Department of Electrical and Computer Engineering, Tennessee Technological University, United States of America.*
[3] *Department of Data and Information Science, University of Ibadan, Nigeria.*
[4] *Department of Statistics, University of Ilorin, Nigeria. 0009-0007-1497-7348*
[5] *Department of Economics, Lingnan University, Hong Kong. 009-0005-0199-0880.*
[6] *Department of Mathematics and Statistics (Data Science) CAS, American University, Washington, DC, United States of America.*

World Journal of Advanced Research and Reviews, 2025, 27(02), 461-470

Publication history: Received on 27 June 2025; revised on 04 August 2025; accepted on 06 August 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.27.2.2884

Abstract

This study looks at the impact of artificial intelligence (AI) and machine learning (ML) in increasing financial inclusion through better credit scoring systems, with a focus on rural Nigeria's agricultural industry. Traditional credit models frequently exclude low-income individuals and smallholder farmers since they are based on official credit histories and organised income data. AI/ML-driven models, which use alternative data such as mobile transactions and utility bills, provide a more comprehensive approach to creditworthiness assessment. The review examines key algorithms such as logistic regression and random forests, as well as their benefits and ethical concerns, such as data privacy, algorithmic bias, and transparency. It also showcases real-world applications, such as Carbon in Nigeria and mobile-based loans in Kenya, which demonstrate better access to credit. However, significant challenges remain, such as digital illiteracy, inadequate infrastructure, and insufficient regulatory frameworks. According to the paper, while AI has great promise, its success is dependent on supportive policy, ethical oversight, and investments in digital infrastructure. Future study should look at the true impact of digital credit instruments on rural lives, as well as how these technologies might be tailored to promote social fairness and sustainable development.

Keywords: Digital scoring tools; Financial inclusion; Artificial Intelligence; Machine Learning; Rural Nigeria

1. Introduction

With billions of people and small companies without access to basic financial services, financial inclusion continues to be one of the most urgent global issues (Mhlanga, 2021). Economic inequities are either exacerbated or lessened in large part by credit scoring systems, which are typically used to evaluate creditworthiness. Large segments of the population that work in informal economies or lack traditional financial resources are excluded by these systems' reliance on traditional data sources, such as credit history and formal employment, even though they are crucial for assessing eligibility for loans and credit products (Mhlanga, 2021). Making savings, payment, credit, and insurance services accessible and sustainable for historically underprivileged people and enterprises is the goal of financial inclusion (Demirgüç-Kunt, Klapper, Singer, Ansar, & Hess, 2020). By enabling them to manage risks, take advantage of opportunities, and live better lives, people also realise that it is a crucial tool to combat poverty and boost the economy (World Bank, 2020). Financial exclusion is a persistent barrier in rural Nigeria, particularly for women and the

* Corresponding author: Babarinde Taofeek Olajide

unorganised sector (EFInA, 2020). Stakeholders are utilising technology to address this issue and assist more individuals in achieving financial inclusion. Financial services and operations now depend on new digital tools as a result of Nigeria's financial sector's fast digitisation.

Mobile banking, fintech initiatives, digital payments, and electronic wallets are a few examples of digital advancements that have a significant impact on how Nigerians interact with financial services today. Thanks to mobile phones and increased internet connectivity, a growing number of people who previously did not receive formal financial services are now receiving digital financial services (DFS). Although digitalisation may thrill individuals, its effects on financial inclusion are not always readily apparent (Muthiora & Ndung'u, 2020). Institutions and policymakers need to have reliable ways to determine whether digitalisation is assisting people in connecting to the internet or if it has left some people behind.

Traditional credit scoring's exclusionary nature exacerbates economic inequality in emerging nations by denying low-income people and small enterprises the resources they need to expand, invest, or deal with financial shocks (FRB, 2021). Access for marginalised people is still restricted by systemic injustices including algorithmic biases and redlining, even in affluent economies (Bartlett et al., 2021). Financial systems must change to take into account a variety of data sources and cutting-edge techniques for determining creditworthiness in order to overcome these discrepancies. Potential remedies are provided by emerging technologies like artificial intelligence [AI] and alternative data analytics. Credit scoring systems can be made more inclusive and representative by utilising non-traditional measures such as energy bills and rental payments. This will lower systemic obstacles to financial access (Schuetz, 2019).

2. Conceptual Framework

Financial inclusion is defined by the United Nations (UN) Millennium Development Goal Summit of 2010 as universal access to a broad range of financial services, offered by several reliable and sustainable organisations, at a fair price. There are differences in the degree of financial inclusion across the globe. In contrast to financial exclusion, which occurs when financial services are unavailable or unaffordable, financial inclusion, also known as inclusive financing, refers to the provision of financial services at reasonable prices to underprivileged and low-income groups within society. Financial inclusion, according to Chakravarty et al. (2013), is the process by which mainstream institutional players ensure that all societal segments, including weaker segments, low-income groups, and vulnerable groups like women have fair, transparent, and affordable access to the financial products and services they need. The process through which institutional actors guarantee equitable, transparent, and reasonably priced access to suitable financial services for all financially disadvantaged individuals and businesses is known as financial inclusion (Chakravarty & Pal, 2013; Johnson and Arnold 2012; Triki Faye 2013; Demirguc-Kunt et al., 2014; Popescu, 2019 Lentner et al., 2020; Oshora et al., 2021).

2.1. Dimensions of Financial Inclusion

Sarma (2008) conducted a study that aimed to create an indicator of financial inclusion based on three factors: the penetration of the banking system, user accessibility, and actual usage across a cross-section of nations. Furthermore, according to some researchers, supply-side aggregate data can be used to estimate financial inclusion characteristics primarily based on formal financial services availability and consumption (e.g. Honohan, 2008; Sarma, 2008, 2012; Chakravarty & Pal, 2010). At the individual level, however, Kunt & Klapper (2013) suggested an index based on demand-side data that concentrates on a number of usage- and barrier-related characteristics separately. Nevertheless, while tracking these metrics separately is helpful, it does not provide a thorough picture of the degree of financial inclusion in various nations (Sarma, 2012).

Based on a few viewpoints, Aduda & Kalunda (2012) provided a quick overview of the aspects of financial inclusion. According to Hannig & Jansen (2010), there are four ways to quantify financial inclusion in order of severity. The first is access, which is the capacity to utilise the financial services and goods offered by official institutions. The second factor is quality, which has to do with how well the financial service or product fits the customer's lifestyle requirements. Thirdly, usage should concentrate more on the longevity and breadth of financial service and product use than just the simple acquisition of banking services. Last but not least, impact involves quantifying how much a consumer's life has changed as a result of using a financial product or service. This data can come from the supply side, which is the level of a financial institution, or the demand side, which is the level of an individual, household, or business, or from a combination of the two.

Additionally, Cámara and Tuestain (2014) developed new metrics to gauge the level of financial inclusion. Two folds are the primary emphasis of these measurements. To start, a parametric approach has been used to calculate each indicator's contribution to their financial inclusion index. One benefit is that it doesn't use any subjective, external data.

Second, it has created a thorough index that incorporates data from the supply and demand sides. According to their estimates, the most crucial factor in determining the degree of financial inclusion is access. According to their findings, an index's explanation depends more on the availability of formal financial services than on the number of users.

Furthermore, according to Chattopadhyay (2011), an IFI must meet a number of requirements in order to be regarded as a decent index. It should, first and foremost, include data on as many facets (dimensions) of inclusion as feasible. Secondly, it should be straightforward and easy to calculate. Lastly, it need to be comparable among nations or states. Based on the World Bank financial inclusion index created by Demirgüç-Kunt and Leora Klapper in 2012, the researcher primarily focusses on financial inclusion features in the current research setting. These metrics are impact, quality, utilisation, and accessibility.

2.2. Financial Access

Interest in financial inclusion and access to capital has grown globally, especially in countries that are developing or emerging. Because of the potential negative effects on growth, income distribution, and poverty levels, among other things, policymakers are becoming more and more concerned about the advantages of financial intermediation and markets that are not widely dispersed throughout the population and across economic sectors (Beck et al., 2007; Sarma and Pias, 2011; Cámara & Tuesta, 2014). They might also be worried about the possible harm to macro stability that could result from the concentration of financial system assets in a small number of people, businesses, or industries. Financial access is the process by which people and businesses enter financial institutions to obtain services (DemirgKunt & Klapper, 2013). This makes it possible to invest, save for retirement, take advantage of possibilities for business, and get insurance against hazards (Demirgüç-Kunt, Beck, and Honohan 2008). The term "access" in the context of this study refers to the availability and capacity to utilise formal financial services and products in order to meet one's daily financial needs (Perera, 2015).

2.3. Impact

Researchers looked at how financial services affected people's financial habits and, eventually, their financial well-being. The researchers checked to see if the inclusion resulted in an increase in the individual's financial well-being (Deka, 2015, Ghosh, 2019; Kumari et al., 2020). Therefore, in the current research environment, an individual's use of formal financial services has resulted in a degree of change in their life. There are no widely recognised dimensions or indices created by earlier researchers that correspond with any socioeconomic environment to assess from an individual standpoint, based on the literature that is currently available. Existing dimensions are also up for debate. In order to reduce methodological issues and determine which dimension is most important among others, suitable dimensions should be created for the current study.

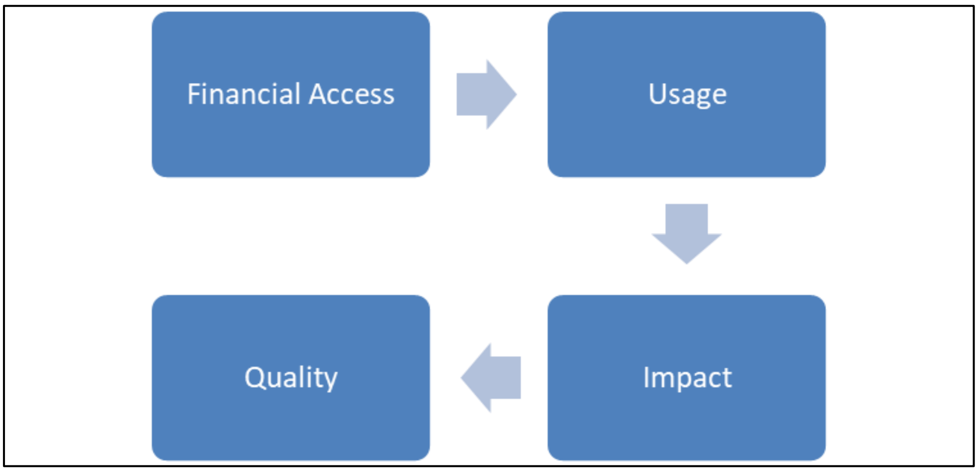

Figure 1 Representation of four dimensions of financial inclusion

2.4. AI and Machine Learning Overview

A subfield of artificial intelligence (AI) called machine learning (ML) seeks to make it possible for computers and other machines to mimic human learning, carry out tasks on their own, and gradually increase their accuracy and performance as an outcome of knowledge and exposure to more data. Supervised learning, learning without supervision, and reinforcement learning are its three main subcategories. In supervised learning, the learning algorithm receives both the data and the associated labels, or responses. Enabling algorithms to learn from labelled data and generate precise predictions for unlabelled data is the aim of machine learning. Regression analysis, probability estimation, and object recognition are among the tasks that commonly employ this method (Grinblat et al., 2016). AI and ML improve efficiency, fairness, and inclusivity. They have the potential to completely transform credit scoring. Large and varied datasets are analyzed by these technologies to find patterns that conventional approaches frequently miss. For instance, to provide a more thorough and precise evaluation of creditworthiness, AI-driven models might incorporate additional data, such as payment histories, transaction patterns, and social media activity (Oliver and Shapiro, 2019). AI has a huge potential to lessen prejudices. AI models can be trained to recognise and fix historical injustices included in datasets, in contrast to traditional systems that depend on strict criteria. To provide more equitable results, sophisticated algorithms, for example, can identify and correct for systemic trends that harm particular demographic groups (Obermeyer et al., 2019). If used carelessly, the same techniques could, however, exacerbate prejudices. Discriminatory results may result from biassed training data, uncontrolled algorithmic designs, and opaque decision-making procedures. Therefore, even while AI and ML have the potential to be transformational, its use must be carefully monitored and guided by ethical principles to guarantee that it fosters equity and inclusivity (Carroll et al., 2017).

2.5. Machine Learning Algorithm used in Credit Scoring

By analyzing various factors, artificial intelligence has helped financial institutions make better lending decisions through credit risk analysis. ML approaches learn from new inputs, which sets them apart from rule-based scoring methods and models that rely on fixed and predefined equations. Because it enables the evaluation of people with poor credit scores or no credit history at all, the application of such algorithm is especially useful in microfinance. Because each algorithm has pros and cons, it is suitable for specific areas of risk assessment and credit rating.

2.6. Logistic Regression

One of the earliest techniques used in credit scoring is logistic regression, which is also a fundamentally used approach to risk assessment. By specifying the collection of independent factors, such as income, debt to income ratio, and prior repayment behaviour, the logistic regression analysis aims to explain the likelihood of default at a specific level. To ascertain whether applicants fall into the low-risk or high-risk categories, outcomes are then compared to a predetermined criterion. Financial institutions frequently choose logistic regression as their preferred technique for the following main reasons: It is simple to interpret and comprehend. It helps the lender to quantify the impact of each variable on credit risk, which will help the lending institution justify its decisions to both customers and regulators. The assumption that there is a linear connection between independent variables and the chance of default is a limitation of logistic regression, particularly when dealing with complex non-linear financial data (Bańbura et al., 2019).

2.7. Decision Trees and Random Forest

Decision trees are commonly used in credit scoring because of the intricate, non-linear link between borrower variables and credit risk. Microfinance institutions will find it easier to justify their lending decisions when employing this credit scoring method because decision trees are quite simple to comprehend and explain. Nevertheless, decision trees may exhibit poor performance on the testing set but good performance on the training set due to their propensity for overtraining. Other ensemble techniques, including random forest models, have been created to get around this restriction. Several decision trees are used in the random forest algorithm type, each of which is cultivated on a distinct subset of the data set. Because the results are averaged, an ensemble of trees in random forests improves generalisation performance and reduces overfitting (Breiman, 2001).

2.8. Credit Scoring System

2.8.1. Traditional vs Non-traditional Scoring System

As instruments for assessing risk and creditworthiness, traditional credit scoring systems having long being the foundation of financial decision-making. To award people a numerical score, these systems usually use a small amount of financial data, such as credit history, payment patterns, outstanding debts, and credit utilisation rates. This score affects the terms that lenders give and establishes eligibility for credit goods like credit cards and loans (Dastile et al., 2020).

Even though these systems work well for people with pre-existing credit histories, they leave out a sizable portion of the population, especially those living in underprivileged areas. Many people lack the documented financial data needed by traditional models, particularly those in low-income or informal employment sectors. Because of this, they are labelled as "credit invisible," which prevents them from obtaining reasonably priced financial services or products (Rothstein, 2017).

An important advancement in credit assessment is the use of non-traditional data. Conventional methods sometimes exclude people without access to standard financial services since they are based on criteria like formal income and credit history. A more comprehensive picture of a person's financial dependability can be obtained from non-traditional data sources such digital transactions, utility bills, and rental payments (Chen et al., 2023).

Table 1 Differences between traditional and non-traditional credit scoring system

Data Type	Traditional Data	Non-traditional Data
Income	Income from formal job	Earnings from the gig economy and freelancing
Payment history	Repayment of loans and credit card	Utility bills and rent payment
Spending patterns	Transactions involving bank	Mobile money and digital wallets
Assets	Ownership of property	Unofficial investment and savings group
Demographics	Marital status and age	Online activities and social media

2.9. Digital Ecosystems in Nigeria

Sub-Saharan Africa's development is becoming more and more dependent on digital technologies. Fintech platforms, digital identification, and mobile connection are opening up new avenues for financial services, governance, and the digital ecosystem in Nigeria.

2.9.1. Mobile Penetrations and Internet Access

Nigeria tops the continent in mobile connectivity, with over 169000,000 mobile subscribers and more than 140 million users of the internet as of early 2025, according to Technext 2025. The main access method is mobile internet, which is supported by wireless networks using GSM and

2.9.2. Digital Identity Systems

Nigeria's fragmented identity ecosystem continues to evolve. The Bank Verification Number (BVN) system has registered over 60 million users, primarily for financial know your customer (KYC) purposes (TechCabal Insights, 2024). The national identification number (NIN) system is being harmonized with BVN and SIM registration databases, although delays and rural exclusion remain serious issues.

2.9.3. Fintech Expansion and Financial Inclusion

Nigeria's fintech sector is one of the most dynamic in Africa. Companies like Palmpay (35+ million users), Moniepoint (processing about 17 billion naira monthly), Paystack, Opay and Flutterwave offer a wide range of services including payments, credit insurance and savings (Financial Times, 2025: Reuters, 2024).

The rise of mobile money and agent networks now over 1.5 million agents, including rural areas has significantly improved financial access. However, issues such as KYC gaps and low trust in digital currencies in rural areas.

2.10. Case Studies

One of the first companies in Nigeria to use AI in digital lending was Carbon, formerly Paylater. In order to ascertain loan eligibility, AI algorithms analyse smartphone data and behavioural patterns such mobile airtime purchases, geolocation, and transaction frequency. Without the need for guarantors or collateral, Carbon's automated technology generates credit judgements instantly (Carbon, 2023).

The use of machine learning to automate the process in Kenya's microfinance industry is a particularly pertinent case study on AI credit rating. The M Pesa and other mobile money services have expanded quickly to provide a vast amount of financial transaction data that AI models use to assess credit risk. In order to assess borrowers' creditworthiness, Johnson et al. (2018) also employed an AI-based credit rating model using data from their past mobile money transactions, airtime purchases, and bill payment patterns. According to the findings, the AI model may cut non-performing loans by 30% more effectively than conventional credit assessment techniques. The effectiveness of alternative data sources in credit scoring is further demonstrated by the fact that consumers who frequently utilise digital technologies were even more efficient in repaying the loans.

2.10.1. Impact of Financial Inclusion in Rural Agriculture

In a recent study on smallholder farmers in Nigeria, Fawowe (2020) used nationwide representative data to quantify the effect of financial inclusion on agricultural productivity. Regardless of how it is measured, the study found that financial inclusion has a positive and statistically significant impact on agricultural productivity.

Olaniyi (2017) used data collected annually from 1981 to 2014 and the method known as ARDL bounds testing to capture the long- and short-run changes of the relationship between financial inclusion and agriculture in Nigeria. The results revealed that the use of financial services had significant short- and long-term effects on agriculture, demonstrating the need of increasing financial inclusion for rural areas' long-term agricultural development. On the other hand, financial accessibility has very little impact on agricultural expansion. Although there are many benefits to giving peasant farmers access to capital, the takeaway was that it was more crucial to think about how the funds were utilised in rural areas and how they impacted the results that were significant to us. The study concludes that in order to improve financial inclusion, considerably reduce poverty, and promote agricultural development in Nigeria, more traditional and unconventional financial service firms must go back to the land and innovate in the country's agricultural sector.

Financial inclusion helps rural farmers by making it easy for them to get loans, save money, and receive remittances, all of which they can use to participate in successful projects (Demirg€uç-Kunt et al., 2008; Honohan, 2008).

Adeoye (2018) investigated gender inequality and financial inclusion among a group of smallholder horticultural farmers in Nigeria. According to the study, horticultural transformation and value chain development in Nigeria depend heavily on the financial inclusion of smallholder horticultural farmers. However, compared to their male counterparts, women small-scale farmers are more financially excluded, which restricts their participation in the sector. According to the results, there is a large gender gap in financial inclusion at 1%.

2.11. Challenges and Ethical Considerations

It is now simpler for organisations, particularly those in microfinance, to assess the credit risk of borrowers thanks to the growing adoption of artificial intelligence in credit scoring. Regarding the financial sector, artificial intelligence (AI) has reduced loan decline rates, increased the dependability of credit risk models, and enhanced financial access, especially for people who had previously been denied access to banking services. However, in order to successfully use AI to credit rating, there are a few challenges that must be resolved. Regulations and ethics, algorithmic unfairness and fairness, data protection and security, and MFI compatibility issues among the difficulties it poses. When it comes to AI-driven lending systems, these are crucial elements that need to be controlled and conquer in order to show continuously sustainable success.

2.11.1. Data Privacy and Security Concerns

When developing an AI-based credit scoring model, the issue is how to gather, store, and above all secure personal and financial data. Sota AI models for evaluating borrower risk use a variety of data types that are gathered in large quantities, including non-traditional data types like social media, mobile phone usage, and purchasing patterns. Like other forms of big data that support credit risk evaluation, the former also has some risks related to data privacy and protection, such as a lack of awareness of how the borrower's data is collected and used, which raises questions about informed consent and data use (Scott et al., 2024). The growing use of AI credit assessment, which gathers and process personal and scale data without the borrowers' consent, is the source of the ethical debate.

2.11.2. Algorithmic Bias and Fairness Issues

The use of artificial intelligence-based credit scoring technology has drawn criticism for reinforcing bias principles found in earlier financial frameworks of credit rating. Three types of bias exist in AI models: algorithmic bias, which occurs when a model unintentionally or purposely discriminates against certain categories of users or individuals; feature selection; and training data selection. Since bias is learnt directly from data, the AI system that is developed is inevitably discriminatory if the data is biassed in favour of current discriminatory lending practices (Barocas et al., 2021). An AI algorithm trained on historical data of loan denials to women or minority applicants, for example, will continue to act biasedly in the future.

2.11.3. Access Barriers

Although artificial intelligence (AI) has the capacity to improve inclusivity, underprivileged groups may find it difficult to use these tools because of language difficulties, inadequate internet availability, or digital illiteracy. To guarantee equitable adoption, financial institutions need to close these gaps.

2.11.4. Transparency and Accountability

For AI-driven credit scoring systems to be used ethically, transparency and accountability are essential. Many machine learning models, sometimes known as "black-box" systems, are opaque, which makes it difficult to comprehend and describe how they make decisions. When decisions have a detrimental effect on people, this lack of transparency presents ethical questions (Angwin et al., 2016). As a remedy, explainable AI [XAI] tools have surfaced, offering insights into the process by which algorithms generate their results. In order to build trust with users and stakeholders, methods like Shapley Additive Explanations [SHAP] and Local Interpretable Model-Agnostic Explanations [LIME] assist in decomposing complicated models into easily understood parts (Gallegos et al., 2024).

2.11.5. Regulatory and Ethical Considerations

Concerns have been raised about the ethical and legal implications of the decisions made and if the use of artificial intelligence in credit scoring complies with the relevant financial legislation. Most AI models are still incomprehensible, which makes it difficult for regulators and borrowers to understand the reasoning behind lending decisions. This is in contrast to traditional credit-scoring methods, which are based on specific metrics that auditors can easily check (Binns et al., 2022). Since financial institutions are required to be accountable for their lending decisions and decision-making is a very delicate process, one of the main concerns for them is the lack of transparency in AI's judgment to offer loans and credit facilities. As a result, regulatory bodies worldwide have acknowledged the significance of making AI policy judgements that are free from bias. Additionally, governments and financial regulators have called for machine learning credit scoring systems to be non-discriminatory, transparent, and traceable. Well-founded governance frameworks are necessary for lending through AI in financial institutions due to various financial regulations and ethical AI practices. Additionally, it has been proposed that regulatory sandboxes, where supervisors are present, serve as a model for applying AI credit scoring prior to its introduction in financial institutions.

3. Policy, Governance, and Infrastructure Considerations

3.1. Enabling Environment

A robust enabling environment created by suitable policies, efficient governance, and sufficient infrastructure is necessary for the success of machine learning (ML) and artificial intelligence (AI)-driven credit scoring tools in rural Nigeria. These components are essential to guaranteeing that smallholder farmers actually benefit from and are reached by technological innovation.

It is essential to have a supporting policy framework. Digital financial services can help close the gap between rural and urban areas, according to Nigeria's National Financial Inclusion Strategy (CBN, 2018). Fintech sandboxes are one example of a regulatory innovation that can assist test AI credit models while safeguarding consumers. Nigeria's data protection laws, especially the Nigeria Data Protection Regulation (NITDA, 2019), also need to change in order to secure the personal information that AI systems use to assess credit. Public-private collaborations that integrate community networks, fintech know-how, and government outreach are also necessary to create an enabling environment. To guarantee that customers comprehend and have faith in AI-based credit solutions, it is vital to invest in digital literacy, financial education, and farmer training. Pilot projects, policy testing, and capacity building can all be further supported by international development partners.

3.2. Research Gaps and Future Directions

Despite how digitalization and machine learning can climb toward financial inclusion, certain conceptual issues have still not been solved. Large parts of the research prioritize numbers, for example, mobile wallets or accounts, without exploring the real impact on people’s lives from the services. Studies have found a gap in learning how much digital financial inclusion affects things like household welfare, business prosperity and local strength. Many of these tools are applied in private sectors such as for credit risk analysis and fraud detection, unlike their applications focused on public policy or improving social results. In order to overcome these gaps, future scientific work could analyze how machine learning might give us new knowledge about behavior patterns, for example understanding why some people still do not benefit from DFS and which factors from society or culture influence digital credit scoring system use. We can further research how models can support the development of helpful financial options that include insurance, pensions and savings for people living on low income.

4. Conclusions

This study highlights the potential of AI and machine learning to revolutionize credit scoring and advance financial inclusion in rural Nigeria's agricultural sector. By leveraging alternative data, AI models can overcome the exclusionary limitations of traditional systems and extend credit access to underserved populations. However, realizing this potential requires addressing critical challenges, including data privacy, algorithmic bias, and infrastructural deficits. A supportive policy environment featuring ethical governance, regulatory innovation, and stakeholder collaboration is essential to ensure fair and transparent deployment. Future research should focus on the real-world impacts of digital credit tools on rural livelihoods and explore strategies to align technological innovation with social equity and sustainable development.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Adeoye, I. (2018). *Financial inclusion and gender disparity among selected smallholder horticultural farmers in Nigeria*. Proceedings of the 36th Annual Conference of Horticultural Society of Nigeria (Hortson), Lafia.

[2] Aduda, J., & Kalunda, E. (2012). Financial inclusion and financial sector stability with reference to Kenya: A review of literature. *Journal of Applied Finance & Banking, 2*(6), 95–120.

[3] Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016). Machine bias. *ProPublica*. https://www.propublica.org/

[4] Barocas, S., Hardt, M., & Narayanan, A. (2021). Fairness in machine learning: Lessons for AI credit scoring. *Financial Data Science Journal, 22*(1), 78–103.

[5] Bartlett, R., Morse, A., Stanton, R., & Wallace, N. (2021). Consumer-lending discrimination in the FinTech era. *NBER Working Paper Series*, w29364. https://doi.org/10.3386/w29364

[6] Beck, T., Demirgüç-Kunt, A., & Martinez-Peria, S. (2007). Reaching out: Access to and use of banking services across countries. *Journal of Financial Economics, 85*(1), 234–266.

[7] Binns, R., Veale, M., & Van Kleek, M. (2022). Transparency in AI decision-making: Ethical challenges for financial institutions. *AI & Society, 37*(4), 789–811.

[8] Carroll, C. D., Slacalek, J., Tokuoka, K., & White, M. N. (2017). The distribution of wealth and the marginal propensity to consume. *Quantitative Economics, 8*(3), 977–1020. https://doi.org/10.3982/QE694

[9] Carbon. (2023). *How Carbon uses data to improve lending in Africa*. https://getcarbon.co

[10] Chakravarty, S., & Pal, R. (2010). Measuring financial inclusion: An axiomatic approach.

[11] Chakravarty, S. R., & Pal, R. (2013). Financial inclusion in India: An axiomatic approach. *Journal of Policy Modeling, 35*(5), 813–837.

[12] Chattopadhyay, S. (2011). *Financial inclusion in India: A case-study of West Bengal*.

[13] Chen, Y., Clayton, E. W., Novak, L. L., Anders, S., & Malin, B. (2023). Human-centered design to address biases in artificial intelligence. *Journal of Medical Internet Research, 25*, e43251.

[14] Dastile, X., Celik, T., & Potsane, M. (2020). Statistical and machine learning models in credit scoring: A systematic literature survey. *Applied Soft Computing, 91*, 106263.

[15] Deka, P. P. (2015). Financial literacy and financial inclusion for women empowerment: A study. *International Journal of Applied Research, 1*(9), 145–148.

[16] Demirgüç-Kunt, A., Beck, T., & Honohan, P. (2008). *Finance for all? Policies and pitfalls in expanding access*. World Bank.

[17] Demirgüç-Kunt, A., Kane, E. J., & Laeven, L. (2014). *Deposit insurance database* (No. w20278). National Bureau of Economic Research.

[18] Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2020). *The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. World Bank.

[19] Demirgüç-Kunt, A., & Klapper, L. (2012). Measuring financial inclusion: The global Findex database. *Policy Research Working Paper No. 6025*. World Bank.

[20] Demirgüç-Kunt, A., & Klapper, L. (2013). Measuring financial inclusion: Explaining variation in use of financial services across countries and within countries. *Brookings Papers on Economic Activity*, Spring.

[21] EFInA. (2020). *Access to financial services in Nigeria 2020 survey*. Enhancing Financial Innovation & Access.

[22] Fawowe, B. (2020). The effects of financial inclusion on agricultural productivity in Nigeria. *Journal of Economic Development, 22*(1).

[23] Ferrara, E. (2023). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *Sci, 6*(1), 3.

[24] Financial Times. (2025). *Palmpay thrives on cash competition*. https://www.ft.com/content/f9b5a77-3565-4c0a-91f1-d78fc63659ae

[25] Gallegos, I. O., Rossi, R. A., Barrow, J., Tanjim, M. M., Kim, S., Dernoncourt, F., Yu, T., Zhang, R., & Ahmed, N. K. (2024). Bias and fairness in large language models: A survey. *Computational Linguistics*, 1–79.

[26] Ghosh, S. (2019). Biometric identification, financial inclusion and economic growth in India: Does mobile penetration matter? *Information Technology for Development* (Unpublished).

[27] Grinblat, G. L., Uzal, L. C., Larese, M. G., & Granitto, P. M. (2016). Deep learning for plant identification using vein morphological patterns. *Computers and Electronics in Agriculture, 127*, 418–424.

[28] Hannig, A., & Jansen, S. (2010). Financial inclusion and financial stability: Current policy issues. *ADBI Working Paper 259*. Asian Development Bank Institute.

[29] Honohan, P. (2008). Cross-country variation in household access to financial services. *Journal of Banking, 32*(11), 2493–2500.

[30] Johnson, S., & Arnold, M. (2018). Digital credit scoring and microfinance: A case study of AI adoption in Kenya. *African Journal of Economic Policy, 25*(2), 123–145.

[31] Johnson, S., & Arnold, S. (2012). Inclusive financial markets: Is transformation under way in Kenya? *Development Policy Review, 30*(6), 719–748.

[32] Kumar, B., & Mohanty, B. (2011). Financial inclusion and inclusive development in SAARC countries with special reference to India. *Vilakshan: The XIMB Journal of Management, 8*(2), 13–22.

[33] Kumari, D. A. T., Ferdous Azam, S. M., & Siti Khalida. (2020). Financial literacy: As a tool for enhancing financial inclusion among rural population in Sri Lanka. *International Journal of Scientific & Technology Research, 9*(4).

[34] Kumari, D. A. T., & Ferdous Azam, S. M. (2019). The mediating effect of financial inclusion on financial literacy and women's economic empowerment: A study among rural poor women in Sri Lanka. *International Journal of Scientific & Technology Research, 8*(12).

[35] Lentner, C., Vasa, L., & Hegedus, S. (2020). The assessment of financial risks of municipally owned public utility companies in Hungary between 2009 and 2018. *Montenegrin Journal of Economics, 16*(4), 29–41.

[36] 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*.

[37] Moscato, V., Picariello, A., & Sperlí, G. (2021). A benchmark of machine learning approaches for credit score prediction. *Expert Systems with Applications, 165*, 113986.

[38] Muthiora, B., & Ndung'u, N. (2020). *Harnessing digital financial services for Kenya's development*. FSD Kenya. https://www.fsdkenya.org

[39] Nairametrics. (2025). *Smartphone penetration set to hit 65% by 2026*. https://nairametrics.com

[40] National Information Technology Development Agency (NITDA). (2019). *Nigeria Data Protection Regulation (NDPR)*. https://nitda.gov.ng

[41] Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science, 366*(6464), 447–453. https://doi.org/10.1126/science.aax2342

[42] Oliver, M., & Shapiro, T. M. (2019). *Black wealth/white wealth: A new perspective on racial inequality*. Routledge.

[43] Olaniyi, E. (2017). Back to the land: The impact of financial inclusion on agriculture in Nigeria. *Iranian Economic Review, 21*(4), 885–903.

[44] Oshora, B., Desalegn, G., Gorgenyi-Hegyes, E., Fekete-Farkas, M., & Zeman, Z. (2021). Determinants of financial inclusion in small and medium enterprises: Evidence from Ethiopia. *Journal of Risk and Financial Management, 14*(7), 286.

[45] Perera, R. (2015). Advancing inclusive financial system in the next decade. In Min B. Shrestha (Ed.), *The SEACEN Centre* (pp. 213–248).

[46] Popescu, A. D. (2019). Empowering financial inclusion through FinTech. *Social Sciences and Education Research Review, 6*(2), 198–215.

[47] Reuters. (2024). *Moniepoint raises $110 million*. https://www.reuters.com

[48] Rothstein, R. (2017). *The color of law: A forgotten history of how our government segregated America*. Liveright Publishing.

[49] Sarma, M. (2008). *Index of financial inclusion* (Working Paper No. 215). Indian Council for Research on International Economic Relations.

[50] Sarma, M., & Pais, J. (2011). Financial inclusion and development: A cross-country analysis. *Journal of Economic Literature, 1*(3), 136–145.

[51] Sarma, M., & Pais, J. (2011). Financial inclusion and development. *Journal of International Development, 23*, 613–628.

[52] Sarma, M. (2012). Index of financial inclusion – A measure of financial sector inclusiveness. *Berlin Working Papers on Money, Finance, Trade and Development*, Working Paper No. 07/2012.

[53] Schuetz, J. (2019). The legacy of redlining: The long-term consequences of discriminatory housing policies. *Brookings Institution*.

[54] Scott, M. L., Bone, S. A., Christensen, G. L., Lederer, A., Mende, M., Christensen, B. G., & Cozac, M. (2024). Revealing and mitigating racial bias and discrimination in financial services. *Journal of Marketing Research*.

[55] Technext. (2025). *Nigeria's digital identity landscape*. https://technext24.com

[56] TechCabal Insights. (2024). *Nigeria's digital identity landscape*. https://insights.techcabal.com

[57] Triki, T., & Faye, I. (2013). *Financial inclusion in Africa*. African Development Bank.

[58] World Bank. (2020). *Global financial development report: Financial inclusion*. World Bank Group.