

Evaluating the Impact of Digitalization on Financial Inclusion in Nigeria: A Machine Learning Approach

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Abstract

This work investigates the ways in which digital technology is helping people in Nigeria to get access to financial service, by applying machine learning to examine this relationship. Helping the poor and growing the economy with financial inclusion still proves difficult in Nigeria, mainly affecting people living in rural areas, white females and those who work informally. The fast uptake of digital financial services can help fill this gap by making finance more affordable and accessible for those who usually do not use banks. Even so, there is little research into how machine learning helps understand this impact. By using machine learning tools, the research watches for trends in financial behavior, tries to identify why some people adopt certain services and seeks out infrastructure, knowledge and rules issues. The research also analyses theories called TAM and DOI that help explain why DFS is now used more widely. According to the findings, digitalization can greatly increase inclusion in financial systems as long as ethical issues in machine learning are considered. Suggestions are; making rural services better, making financial literacy more common and encouraging everyone involved to cooperate for inclusive growth. The study adds value by bringing together machine learning insights and measures for public policy, helping to learn more about how digitalization can help Nigeria achieve financial inclusion in a sustainable way.

Keywords: Financial Inclusion; Digitalization; Machine Learning; Digital Financial Services; Fintech; Poverty Reduction.

1. Introduction

Financial inclusion is about making sure traditionally underserved individuals and businesses have an opportunity to use savings, payment, credit and insurance services affordably and sustainably (Demirgüç-Kunt, Klapper, Singer, Ansar, & Hess, 2020). People also recognize that it is an important way to reduce poverty and grow the economy, by letting them handle risks, make the most of opportunities and live better lives (World Bank, 2020). In rural Nigeria, along with among women and the informal sector, financial exclusion is a long-term obstacle (EFInA, 2020). In Answering this challenge, stakeholders are using technology to help more people reach financial inclusion. The financial sector in Nigeria is rapidly digitalizing, so financial services and operations now rely on new digital tools. Among the digital developments are mobile banking, fintech programmes, digital payments and electronic wallets which now matter a lot in how Nigerians work with financial services (Nwankwo, 2020). More and more people who were not served by formal finance before are now receiving digital financial services (DFS), because of mobile phones and greater internet access. But while people may be excited about digitalization, it is not always obvious what impact it has had on financial inclusion (Muthiora & Ndung'u, 2020). Policymakers and institutions must have strong methods to find out if digitalisation is helping people to get online or if it has left some behind.

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It is in this situation that machine learning is most valuable. With machine learning, part of artificial intelligence, algorithms and models study big data to discover patterns, predict outcomes and offer valuable insights without having to programme them for each task (Goodfellow, Bengio, & Courville, 2016). Applying machine learning to financial inclusion helps review thousands of mobile transactions, credit files and customers' behaviour, so that we can look at how digital services affect financial access (Manyika, Lund, Chui, Bughin, Woetzel, Batra, Ko, & Sanghvi, 2017). Thanks to machine learning, researchers and policymakers can see which strategies perform best, where digital equity is still lacking and how interventions can be fixed to reach inclusion goals (Bruhn & Love, 2014).

The main objectives of this research are to explore how digitalisation has influenced financial inclusion in Nigeria, investigate the role of machine learning in evaluating this impact, and identify how machine learning insights can inform better policy and practice. The central research questions are: How has digitalization advanced or hindered financial inclusion in Nigeria? What advantages does machine learning offer for analysing its impact? And how can findings from machine learning models help improve strategies for inclusive finance?

2. Conceptual Clarifications

Digitalization is the application of technology to combining, structuring and applying processes, services and business methods for better efficiency, easier access and greater innovation, according to Brennen and Kreiss (2016). To help financial products become more accessible and well delivered, financial services use mobile apps, online systems, digital payments, blockchain and fintech solutions (Gomber, Koch, & Siering, 2017). Financial inclusion means helping low- and marginalised income people get access to and regularly use financial services they can compose (Sarma, 2016). Access to financial services is evaluated alongside the regularity with which people deposit, withdraw, borrow, insure or make payments officially (Demirgüç-Kunt et al., 2015).

A computer using machine learning can figure out how to improve from data, predict outcomes or make decisions on its own, without being programmed anticipate each possibility (Bishop, 2006). With classification, regression or clustering, researchers can find patterns, predict what will happen and make decisions from data sets that are difficult to analyse (Hastie, Tibshirani, & Friedman, 2009). DFS is used to describe financial services that are accessed and delivered through things like mobile money, internet banking, e-wallets and making electronic payments. DFS give fast, inexpensive and easy-to-use financial options to those who can't take advantage of regular banking (Suri & Jack, 2016).

Connecting digitalization to financial inclusion is not difficult but is quite complex. Because of digitalization, it has become easier for people to join the formal financial system by overcoming problems such as being far from services, paying high fees or not having official identification. Not everyone has to open a bank account or travel to a branch because mobile money services make it possible to safely save and send money on your phone (Jack & Suri, 2014). Thanks to technology, anyone working in small businesses can now access adapted microcredit, insurance and investment services (Beck, Demirgüç-Kunt, & Honohan, 2009). Still, financial inclusion using technology works best when people are digitally literate, can use mobile devices, pay reasonable data costs and have trust in electronic systems (Lokshin, Ravallion, & Datt, 2020). This work uses machine learning approaches to explore how these affecting elements play a role in financial inclusion in Nigeria as well as to locate places where there are advantages and challenges.

3. Theoretical Framework

Several key theories show how digitalization supports the goal of financial inclusion. It is widely believed that the Technology Acceptance Model (TAM) found by Davis in 1989 inspires people's use of technology, as people weigh the usefulness against how easy the technology stands to adopt. By using TAM, researchers can find out why people use or avoid digital financial services based on how practical and convenient they think those services are (Ogunleye et al., 2020). A further useful theory is Diffusion of Innovation (DOI) developed by Rogers (2003), explaining how new concepts, products or technologies are taken up by groups over the years. DOI looks at how the introduction of fintech solutions can be helped by the actions of early adopters, social contacts and means of communication. How digital financial products spread in Nigeria can tell us why some groups are quicker to accept them than others.

In the summary, the Financial Intermediation Theory by Gurley and Shaw (1960) says that financial institutions help link savers with borrowers, improving the useful way resources are allocated in the economy. More uses of technology allow intermediation in banking to be cheaper, smoother and give options such as peer-to-peer lending and digital microfinance which exclude traditional banks. All these theories explain how digitalization helps financial inclusion by

changing how people respond to new technologies, encouraging quick spread of innovation and introducing different players into the financial industry.

4. Review of Related Concepts

4.1. Digital Transformation in Finance

Nigeria's financial services have been transformed by the advance of fintech, mobile money, digital banking and e-wallets. Using new technology, fintech companies provide digital ways to manage money, take out loans, build savings and get insurance, frequently aiming at serving people without enough access to banking services. Mobile money makes it possible to store and move money from phones which helps reduce people's need for cash and account with a bank. Customers can now use online and mobile digital banking to access all the usual banking services more easily (Nwankwo, 2020). Having an e-wallet makes it possible to pay electronically, put money aside and use different kinds of services every day. This collection of new technologies helps overcome many hurdles in regular banking, providing both low-cost and flexible services to include more people.

4.2. Barriers to Financial Inclusion in Nigeria

Even with advancements, some problems mean many people do not yet have access to financial services. Because electricity, internet and mobile reception are unreliable in many rural areas, ongoing use of digital services is not possible for many (EFInA, 2020). Poor understanding of financial and digital topics makes it hard for many to make use of apps or grasp how financial items operate (Demirgüç-Kunt et al., 2020). Existing rules for verifying customers and unclear laws restrict both how fintech companies operate and the ability of unbanked people to go through official channels. Concerns over possible fraud, online crime and the privacy of their data are constantly stopping people from trying digital financial services (Boateng et al., 2020). Eliminating these obstacles allows digitalization to achieve real and valuable financial inclusion.

4.3. Opportunities through Machine Learning

Some of these challenges can be handled and financial inclusion outcomes boosted by using machine learning. With data analysis, financial institutions can recognise customers' tendencies, likes and requirements and therefore create services that perfectly meet those needs (Manyika et al., 2017). Using predictive analytics, lenders can recognise borrowers who are likely to default, reaction before the default and ensure the loans are maintained. Machines help providers create groups of users with specific traits, like the way people use banking services or their preferences and design solutions that address those groups uniquely (Ngai et al., 2009). In addition, using behaviour data from mobile phones or social media, lenders can now assess creditworthiness, offering loans to many people who did not have formal records before (Björkegren & Grissen, 2020). In general, machine learning improves how things are done and allows financial service providers to develop cleverer, more inclusive services.

5. Machine Learning in Financial Inclusion Research

Machine learning is becoming more common in financial services around the world to help banks work more effectively, decide better and enhance customer experience (Begenau et al., 2020). In credit scoring, detecting fraud, organizing customers into groups and making personalized marketing decisions, machine learning models can go through lots of data to reveal patterns and make predictions that older techniques find difficult (Fuster et al., 2020). Alternative data such as mobile phone data and utility billing, is commonly used by fintech companies to make lending decisions to people who have never had formal credit before (Berg et al., 2020). Machines trained with data analyze transaction behavior, lowering the chance of fraud for banks (Dal Pozzolo et al., 2015). Risk assessment changes dynamically for insurers and the likely impacts of financial regulations are modelled by policymakers.

Machine learning is considered particularly important for growing financial inclusion in Nigeria (Ojo et al., 2020). First, analyzing transactions, data about where people live and social aspects help predict unmet needs, so actions can be taken to assist those individuals more effectively. By using machine learning, companies can uncover which channels, products or groups are likely to help the most with adoption, so they can expand more affordably.

Even so, there are advantages and disadvantages to using machine learning in this area. Machine learning helps large companies analyze a wide variety of data at a low price and improves how they aim their marketing and make decisions (Agrawal et al., 2019). With data, firms can change their plans in real time and adapt as required (Brynjolfsson & McElheran, 2019). At the same time, because machine learning models are sometimes too complicated, they worry some

experts about how transparent and fair they are (Doshi-Velez & Kim, 2017). They can sometimes strengthen biases due to fact that existing problems in the data might sideline the groups they seek to involve. On top of that, Nigerian organizations must have the technology, use strong data resources and ensure their work follows ethical and privacy rules, all of which are major challenges in many parts of the country.

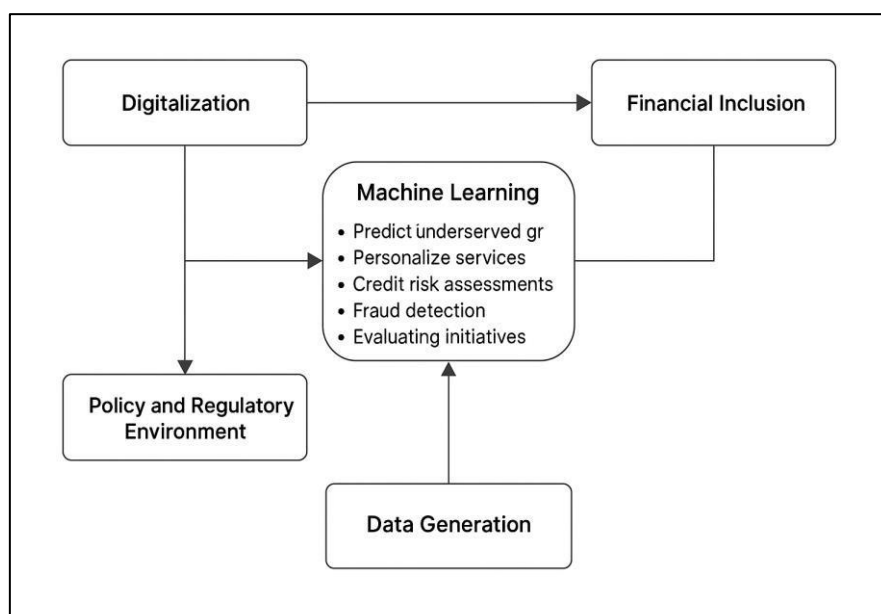


Figure 1 A flow chart showing the relationship between digitalization, financial inclusion, and machine learning

6. 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 DFS 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.

Testing proposals about which combinations are most likely to maintain financial inclusion for the longest period is another important future research focus. Experts could explore the ethical issues linked to data-supported financial services and find solutions for balancing new technologies, fairness, clarity and privacy. The results showed where future studies can help improve both efficiency and social benefits of financial inclusion through machine learning in Nigeria.

7. Conclusion

By using machine learning, the study finds that digital solutions can advance financial inclusion in Nigeria by analyzing a huge amount of data. With mobile money and fintech becoming available, underserved populations can access financial services more easily, although difficulties such as poor infrastructure, low computer skills and rules from the government are still a problem. Using machine learning, barriers can be handled by giving customized experiences, predicting consumer behavior and saving resources. However, to avoid any unequal results, ethical problems such as bias and transparency, should be dealt with. The results make it clear that overcoming financial exclusion requires balancing technology with solutions to existing imbalances.

Recommendations

Improving infrastructure in rural parts of a country should be a main priority for policymakers, helping to assure that everyone has easy access to internet and electricity. Programmes that teach about finances should be scaled up to help people use digital systems. Rules must get updated to help new tech grow and protect consumers and their data. To reduce bias in machine learning, financial organizations should introduce ethical AI practices. Teamwork among fintech, banks and government organizations is important for including everyone in financial services. Investigations moving forward should mainly look at long-term results of digital financial services for those living in poverty.

References

- [1] Agrawal, A., Gans, J., & Goldfarb, A. (2019). *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Press.
- [2] Beck, T., Demirgüç-Kunt, A., & Honohan, P. (2009). Access to financial services: Measurement, impact, and policies. *The World Bank Research Observer*, 24(1), 119-145.
- [3] Begenau, J., Farboodi, M., & Veldkamp, L. (2020). Big data in finance and the growth of large firms. *Journal of Monetary Economics*, 125, 171-192.
- [4] Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. *Review of Financial Studies*, 33(7), 2845-2897.
- [5] Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.
- [6] Björkegren, D., & Grissen, D. (2020). Behavior revealed in mobile phone usage predicts credit repayment. *The World Bank Economic Review*, 34(3), 618-634.
- [7] Boateng, R., Heeks, R., Molla, A., & Hinson, R. (2020). Digital commerce and development: Does the growth of e-commerce promote development? *Information Technology for Development*, 27(1), 1-14.
- [8] Brennen, J. S., & Kreiss, D. (2016). Digitalization. In *The international encyclopedia of communication theory and philosophy* (pp. 1-11). Wiley.
- [9] Bruhn, M., & Love, I. (2014). The real impact of improved access to finance: Evidence from Mexico. *The Journal of Finance*, 69(3), 1347-1376.
- [10] Brynjolfsson, E., & McElheran, K. (2019). The rapid adoption of data-driven decision-making. *American Economic Review*, 109(5), 133-139.
- [11] Dal Pozzolo, A., Boracchi, G., Caelen, O., Alippi, C., & Bontempi, G. (2015). Credit card fraud detection: A realistic modeling and a novel learning strategy. *IEEE Transactions on Neural Networks and Learning Systems*, 29(8), 3784-3797.
- [12] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340.
- [13] Demirgüç-Kunt, A., Klapper, L., Singer, D., & Van Oudheusden, P. (2015). *The Global Findex Database 2014: Measuring financial inclusion around the world*. World Bank.
- [14] 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.
- [15] Doshi-Velez, F., & Kim, B. (2017). *Towards a rigorous science of interpretable machine learning*.
- [16] EFINA. (2020). *Access to financial services in Nigeria 2020 survey*. Enhancing Financial Innovation & Access.
- [17] Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., & Walther, A. (2020). Predictably unequal? The effects of machine learning on credit markets. *Journal of Finance*, 77(1), 5-47.
- [18] Gomber, P., Koch, J.-A., & Siering, M. (2017). Digital finance and fintech: Current research and future research directions. *Journal of Business Economics*, 87(5), 537-580. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- [19] Gurley, J. G., & Shaw, E. S. (1960). *Money in a theory of finance*. The Brookings Institution.
- [20] Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). Springer.

- [21] Jack, W., & Suri, T. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review*, 104(1), 183-223.
- [22] Lokshin, M., Ravallion, M., & Datt, G. (2020). Understanding the drivers of financial inclusion: Evidence from India. World Bank Policy Research Working Paper No. 9297. Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., & Sanghvi, S. (2017). Jobs lost, jobs gained: Workforce transitions in a time of automation. McKinsey Global Institute. <https://www.mckinsey.com/mgi>
- [23] Munyegera, G. K., & Matsumoto, T. (2016). Mobile money, remittances, and household welfare: Panel evidence from rural Uganda. *World Development*, 79, 127-137.
- [24] Musa, A. S., Olalere, M., & Adebisi, A. A. (2020). Machine learning applications in financial inclusion: A focus on the Nigerian market. *Journal of Financial Technology*, 6(1), 45-62
- [25] Muthiora, B., & Ndung'u, N. (2020). Harnessing digital financial services for Kenya's development. FSD Kenya. <https://www.fsdkenya.org>
- [26] Ngai, E. W., Xiu, L., & Chau, D. C. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. *Expert Systems with Applications*, 36(2), 2592-2602.
- [27] Ogunleye, G. O., Adeyeye, P. O., Oladipo, T. B., & Adeoye, A. O. (2020). Technology acceptance model and financial inclusion: Evidence from mobile money users in Nigeria. *African Journal of Science, Technology, Innovation and Development*, 12(6), 771-781.
- [28] Ojo, T. B., Adetunmbi, A. O., & Falaki, S. O. (2020). Artificial intelligence for financial inclusion in Nigeria: Prospects and challenges. *African Journal of Computing & ICT*, 15(1), 1-14.
- [29] Okolo, C. T., Mbarika, V., & Okoye, J. C. (2020). Artificial intelligence for Africa: An opportunity for growth and development. *AI & Society*, 36(2), 429-440.
- [30] Ovia, J. (2020). Digital financial inclusion: Regulatory imperatives for Nigeria. *Journal of Banking Regulation*, 22(3), 228-241. Ozili, P. K. (2020). Digital finance, green finance and social finance: is there a link?. *Financial Internet Quarterly*, 17(1), 1-7.
- [31] Richman, R. (2020). AI in insurance: The 2021 landscape. *Journal of Insurance Regulation*, 40(1), 1-25.
- [32] Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
- [33] Sarma, M. (2016). Measuring financial inclusion. *Economics Bulletin*, 36(1), 604-611.
- [34] Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, 354(6317), 1288-1292. <https://doi.org/10.1126/science.aah5309>
- [35] World Bank. (2020). *Global financial development report: Financial inclusion*. World Bank Group.